A peer-reviewed open-access journal
NeoBiota
Advancing research on alien species and biological invasions

NeoBiota 106: 107–139 (2026)
DOI: 10.3897/neobiota.106.161880

Research Article

Simple network models integrate global change, social dynamics and management interventions in biosecurity scenario analysis

Christopher E. Buddenhagen[1], Christopher McGrannachan[2], Graeme Bourdôt[3], Shona Lamoureaux[3], Karen A. Garrett[4], Geoff Kaine[5], Norman W. H. Mason[5]

1 *Bioeconomy Science Institute, Ruakura Research Centre, Hamilton, New Zealand*
2 *Bioeconomy Science Institute, Auckland, New Zealand*
3 *Bioeconomy Science Institute, Lincoln Research Centre, Lincoln, New Zealand*
4 *Plant Pathology Department and Global Food Systems Institute, Institute of Food and Agricultural Science, University of Florida, Gainesville, USA*
5 *Bioeconomy Science Institute, Hamilton, New Zealand*

Corresponding author: Norman W. H. Mason (MasonN@landcareresearch.co.nz)

OPEN ACCESS

Academic editor:
Jonathan M. Jeschke
Received: 12 June 2025
Accepted: 23 December 2025
Published: 13 March 2026

Citation: Buddenhagen CE, McGrannachan C, Bourdôt G, Lamoureaux S, Garrett KA, Kaine G, Mason NWH (2026) Simple network models integrate global change, social dynamics and management interventions in biosecurity scenario analysis. NeoBiota 106: 107–139. https://doi.org/10.3897/neobiota.106.161880

Copyright: This is an open access article distributed under the terms of the CC0 Public Domain Dedication.

Abstract

Global change and public participation are both areas of considerable uncertainty in estimating the success of biosecurity response strategies, but are poorly integrated in most available scenario analysis frameworks. We introduce *INApest()*, a novel network simulation method which integrates social and global change factors, as well as pest biology and multiple management variables in scenario analyses of biosecurity responses. *INApest()* separates the management response into four key parameters: probability of detection; management adoption; eradication of local populations; spread reduction (e.g. through movement restrictions or hygiene measures). It also permits simulation of biosecurity responses which evolve organically as new incidences of the pest are detected and information about the pest and management technologies spread through the network. We demonstrate selected functionality of *INApest()* using *Nassella neesiana* (Chilean Needle Grass; CNG), a slow-spreading pasture weed that impacts animal health, as a case-study. Realistic historical CNG spread rates are reproduced under a no management scenario using dispersal kernels derived from known natural and human-mediated spread mechanisms. Scenario analyses comparing over 15,000 parameter combinations reveal that communication of invasive threat to farms neighbouring known infestations significantly reduces the farm-scale eradication probability and spread reduction required for management success (i.e. success is achieved at lower levels of farm-scale management practice efficacy). We use targeted simulation experiments to show how *INApest()* permits assessment of cross-border consequences of local management decisions and how communication between landowners interacts with climate change and surveillance effort to impact management success. *INApest()* has the potential to be used at multiple scales and to explore a wide range of management, global change and social scenarios.

Key words: Agriculture, border protection, climate, detection, dispersal, eradication, habitat, invasive species, land use, pasture, pest control, risk assessment, simulation, spread modelling

Introduction

Global change, encompassing shifts in climate, land use and global trade (Hulme 2009; Chapman et al. 2017; Marchioro and Krechemer 2021; Capinha et al. 2023), coupled with socio-economic factors such as public participation and information spread within social networks (Reeve et al. 2000; Kaine and Wright 2022), play pivotal

roles in shaping the spread of pests (used here to refer to all invasive alien species) and influence the success or failure of biosecurity management responses (Yletyinen et al. 2021). While studies often tackle these elements in isolation when addressing invasive species management, there is a scarcity of simulation tools that comprehensively integrate across factors, such as the biology of the invader, climate change, management efficacy, outreach endeavours and societal involvement (Hulme et al. 2023). The recent Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) invasive species assessment identified the ability to integrate global change factors as a gap in pest response planning and incorporation of social factors as a gap in pest response implementation (Sankaran et al. 2023). The IPBES review also emphasised that objective scenario analysis is seldom employed in pest response planning and implementation, suggesting that we lack accessible, fit-for-purpose scenario analysis tools (Sankaran et al. 2023). Further, a recent horizon scan within the "One Biosecurity" framework noted the need for simulation models which capture the full complexity of invasion processes, management interventions and social factors in pest response planning (Hulme et al. 2023). In this study, we build on existing network-based modelling approaches (Jeger et al. 2007; Pautasso et al. 2010a; Garrett et al. 2018; Cope et al. 2019; Frost et al. 2019; Garrett 2021; Adiga et al. 2022; Runghen et al. 2023) to integrate social and global change factors in a multidimensional pest response framework, with the aim of providing scenario analysis tools which are more likely to be adopted in response planning and implementation.

The need for pest scenario analysis frameworks

Prioritising management effort amongst pests or between sites at risk of invasion is amongst the greatest strategic challenges facing biosecurity systems globally (Panetta 2009; Simberloff 2009; Renteria et al. 2017; Simberloff et al. 2018). Potentially harmful introduced species often establish at multiple sites before detection, by which time eradication may be considered unfeasible (Panetta 2004; Panetta and Lawes 2005). Consequently, for incipient invaders or "sleeper pests", the benefits of control efforts may primarily be via prevention of spread rather than reducing the impacts they have had on the already invaded sites (Bourdôt et al. 2015; Buddenhagen and Tye 2015). Biosecurity planners require robust methods for deciding when and how to intervene and for demonstrating the value of control efforts to potential funders (e.g. stakeholders, central or local governance bodies) and affected communities (Mason et al. 2023).

Scenario analysis is a valuable yet underutilised tool for evaluating management strategies by integrating multiple factors (Wiebe et al. 2018; Sankaran et al. 2023). Regulators and land managers often approach these scenarios as informal thought experiments, rather than using formal models with defined assumptions and objective success criteria (Simberloff 2009; Buddenhagen and Tye 2015; Panetta 2015). Developing flexible, purpose-built frameworks for pest scenario analysis remains a challenge.

Capturing the complexity of pest responses: the multidimensional nature of invasion processes and management responses

Developing fit-for-purpose pest scenario frameworks is challenging due to the need to integrate processes in three key areas: invasive spread (biology), the social dynamics that influence threat awareness and management decisions (social and

cultural) and management effectiveness (management) (Simberloff et al. 2018; Garrett 2021; Sankaran et al. 2023). These three areas are expected to interact to produce different outcomes related to the rate, extent and impact of the invader.

Invasive spread is influenced by interacting elements which are often imperfectly known or hard to predict, including; distributions of initial infestations, connectivity of suitable habitat patches, natural and human-aided dispersal pathways and global change factors, particularly those that affect habitat suitability (Gallien et al. 2010; Panetta et al. 2011; Ferrari et al. 2014; Lustig et al. 2017). Effectiveness of pest management responses is influenced by the ability to detect or correctly identify new infestations, eradicate known infestations and prevent spread through movement restrictions and hygiene measures, such as cleaning farm equipment and footwear, excluding livestock from infested paddocks, restricting livestock movement or voiding livestock gut contents prior to movement (Panetta and Lawes 2007; Simberloff 2009; Panetta et al. 2011; Howell 2012; Buddenhagen and Tye 2015; Liew et al. 2023). Social attitudes to pests (based on perceived impacts to economic or other values) and connectivity within social networks may affect the likelihood that information is shared within social networks, as well as the receptiveness of agents to information either from within the network or external sources (e.g. Buddenhagen et al. 2017; Garrett 2021; Yletyinen et al. 2021).

Interactions between factors influencing invasive spread, management and information sharing create abundant potential for pest management responses to exhibit complex systems behaviour, where *a priori* prediction of outcomes from initial conditions is challenging because similar starting conditions may yield vastly different outcomes (Ferrari et al. 2014; Garrett et al. 2018; Seebens et al. 2019). Simulation-based scenario analyses are well suited to capturing potential complex system behaviour, relative to statistical or deterministic modelling techniques (Jeger et al. 2007; Garrett et al. 2018; Green 2023; Yang et al. 2023).

Many pest prioritisation and planning frameworks incorporate global change factors, especially species distribution models, including those that incorporate climate change (Leung et al. 2012; Phillips et al. 2018; Roigé and Phillips 2021), with some approaches also incorporating natural and human-mediated dispersal processes and basic management variables, such as detection and eradication probabilities (Jamieson et al. 2022). However, frameworks incorporating global change factors often do not consider social factors, such as management adoption probability or the spread of information about pests through social networks (Buddenhagen et al. 2017; Garrett 2021). Socioecological network models define nodes (e.g. geographical locations or agents) and the links between them, representing associations like invasion pathways or links in socioeconomic networks (Sayles et al. 2019; Yletyinen et al. 2021; Rickowski et al. 2025). Network models can integrate biological factors, such as dispersal ecology and habitat suitability and social aspects, like knowledge dissemination and management adoption to permit joint simulation of pest spread between locations and information transfer between human actors (Behr et al. 2017; Buddenhagen et al. 2017; Andersen et al. 2019; Garrett 2021). This makes socioecological network models particularly well-suited to evaluating invasive species management strategies. However, to our knowledge, these models do not explicitly incorporate global change factors, such as climate or land-use change.

Integrating global change and social factors in multidimensional management scenarios

The primary goal of this study was to, for the first time that we are aware of, develop simulation methods capable of integrating across multiple global change and social factors within a multidimensional pest spread and management response framework. To this end, we extend an existing socioecological network modelling framework - Impact Network Analysis (INA) (Garrett 2021). Our novel framework builds on the *INAscene()* function of the INA framework (Table 1) which simulates spread of a bioentity, information about the bioentity (e.g. a pest or a biocontrol agent) and adoption of management to increase or reduce bioentity establishment within socioecological networks . We extend *INAscene()* by adding functionality to: include additional management parameters (detection probability, eradication probability and spread reduction), incorporate global change factors; incorporate social change factors (temporal change in management adoption) and change in management technologies (i.e. through adoption of novel detection, eradication and spread reduction methods). Like *INAscene*(), the framework uses matrix operations to simultaneously simulate the spread of pests and information about pests within socioecological networks. Using the spread of the pest plant *Nassella neesiana* (Trin. & Rupr.) Barkworth (Chilean needle grass; CNG) between pastoral farms within New Zealand as our study system, we present simulation experiments demonstrating the potential of our framework to explore the following questions:

1) What is the relative effect of multiple management variables, the rate of information spread, climate change and interactions between them on pest spread and the likelihood of pest management success?

2) How does the decision to manage a pest in one region impact pest response outcomes in neighbouring regions? How will these benefits be affected by climate change?

3) What is the potential benefit of communication about a pest within social networks for improving management response outcomes under current and future climates?

Methods

INApest: – a new socioecological network modelling framework

We present a new simulation function (Fig. 1) named *INApest()*, which was originally built as a wrapper around the *INAscene()* function of the impact network analysis R package of Garrett (2021). The latest version of *INApest()* uses generic R commands to replace the operations performed by *INAscene()* in order to increase processing speed and flexibility in adding new functionality. Table 1 compares the functionality of *INAscene()* and *INApest()*, with an emphasis on additional functionality provided by *INApest()*. We named our function *INApest()* because our focus is on the biosecurity application of Impact Network Analysis to the management of harmful bioentities, such as pests, weeds and pathogens (for simplicity, we use the term pest to cover all these categories henceforth). Code for the *INApest()* core function is available from a GitHub repository (Mason 2023). A full list of required and optional parameters is provided in the Suppl. material 1.

INAscene() models the spread of both bioentities (e.g. invasive species or biological control agents) and information (about management practices to reduce or

Table 1. Features (functionality) provided by the *INAscene()* function within the impact network analysis (INA) R package (Garrett 2021) and differences in features provided by the new *INApest()* function. Features are grouped into three categories: a) Pest spread, b) Management and c) Information spread. A diagrammatic representation of basic *INApest()* functionality is provided in Fig. 1.

Features	INAscene	INApest difference
a) Pest spread		
Initial invasion. Applied outside time step loop	Binary vector indicating initial presence or absence at each node (length N nodes) or number or proportion of initially infested nodes (to be allocated via random binomial process).	Option to provide a vector (length N nodes) of probabilities either used directly as probabilities in random binomial process assigning infestations or as weights (when number or proportion of infested nodes provided). Permits user-specified variation in probability of initial infestation.
Biophysical adjacency (i.e. dispersal probability) matrix (BPAM)	Single asymmetric matrix (probability of a node being source or destination of invasion with another node can differ). Permits directional spread (e.g. downstream, with prevailing wind or from nursery/ seed supplier/breeder to plantation/farm)	Option to supply separate natural and human-mediated asymmetric matrices
Establishment (i.e. probability of invasion conditional on dispersal).	Not provided as separate probability. There are arguments "probestabmean" "probestabvec" in the function call, but these affect local population persistence, not establishment	Separate probability moderating invasion probability by multiplication with columns of BPAM. Option to provide as mean and standard deviation, vector (length N nodes) or matrix (N nodes x N time-steps). Permits random or user-specified variations between nodes and across time-steps. Allows inclusion of climate and land-use change effects.
Survival (i.e. local population persistence between timesteps): Probability moderating local population survival through multiplication with invasion status vector.	Option to provide as mean and standard deviation or vector of probabilities. Permits random or user-specified variation between nodes.	Option to provide as mean and standard deviation, vector (length N nodes) or matrix (N nodes x N time-steps). Permits random or user-specified variations between nodes and time-step. Allows inclusion of climate and land-use change effects. Applied to extant invasion at the start of each time-step.
External invasion (e.g. from neighbouring regions, through travel or trade shipments)	Affects only initial infestations. Option to provide argument (initbio.dist) determining if initial infestations are distributed at random or in nodes closest to the top edge or right edge of the area.	Option to permit external invasion at each time-step. If external invasion risk provided as matrix permits external invasion risk to vary through time (e.g. in response to spread in neighbouring regions or nations). If external invasion applied at each time-step. it occurs after internal invasion simulation.
b)Management		
Eradication: Probability moderating local population survival through multiplication with invasion status vector. Applied at the start of each time-step	When management effect direction is negative, decreases survival. Option to provide as mean (maneffmean) and standard deviation. Permits random variation between nodes.	Option to provide as mean and standard deviation, vector (length N nodes) or matrix (N nodes x N time-steps). Permits random or user-specified variation between nodes and time-steps. Occurs before internal invasion simulation. Only possible when the land manager has information -see information transfer below.
Management effect direction	Option for management effect on survival to be positive, allowing for management to support conservation	Not included. Assumed that management is neutral or decreases survival
Spread reduction: Probability moderating dispersal between nodes through multiplication with rows of BPAM	Not included	Option to provide as mean and standard deviation, vector (length N nodes) or matrix (N nodes x N times-teps). Permits random or user-specified variation between nodes and time-steps. Occurs before internal invasion simulation. Only possible when the land manager has information.
Detection probability: Probability moderating detection status vector through multiplication with invasion status vector. When a new infestation is detected, detection status is positive until the local (node) population becomes extinct	Not included. Assumes all new infestations are detected in the time-step they establish.	Option to provide as mean and standard deviation, vector (length N nodes) or matrix (N nodes x N time-steps). Permits random or user-specified variation between nodes and time-steps. Occurs before internal invasion simulation.
Management adoption: probability regulating the implementation of management at each node at each time-step.	If management is adopted eradication methods are applied to reduce local population survival. Option to provide as mean and standard deviation. Permits random variation between nodes. Only nodes with information can adopt management.	If management is adopted both eradication (reduction in survival) and spread reduction (reduction in probability of being an invasion source) are applied. Option to provide as mean and standard deviation, vector (length N nodes) or matrix (N nodes x N time-steps). Permits random or user-specified variation between nodes and time-steps. Occurs before internal invasion simulation.
c)Information spread		
Socioeconomic adjacency (i.e. information transfer probability) matrix (SEAM)	Single asymmetric matrix	No difference
Information and management adoption	Only nodes with information can adopt management	No difference
Information transfer	Any node with information can transfer information to other nodes. Information is knowledge of management technologies.	Only nodes that have detected infestations can transfer information. Information is knowledge of the threat of invasion. When detection probability is 0 in all nodes in all time-steps management is never adopted.

Features	INAscene	INApest difference
Management effect threshold for information transfer	If option is selected, a 'science of science' scenario is evaluated: information transfer only occurs if management effect is observed to exceed the threshold for adoption in stochastic simulations. If not, management is never adopted, as in a zero management scenario.	Not included.
External information transfer (e.g. from farm consultants, extension officers, media and social media)	Affects only initial information status. Option to provide argument (initinfo.dist) determining if initial nodes with information are distributed at random or are closest to the top edge or right edge of the area.	Option to permit external information transfer at each time-step. If external information transfer provided as matrix, permits external information transfer to vary through time. If applied at each time-step, it occurs after internal information transfer simulation.

enhance bioentity survival) within socioecological networks (Garrett 2021; Etherton et al. 2025). It also permits inclusion of management adoption probability and eradication probability to model management effectiveness. This functionality potentially provides a great deal of power for assessing competing management strategies for invasive species management in socioecological systems.

INApest() inherits the ability of *INAscene()* to simultaneously simulate the spread of a pest and the spread of information about the pest through socioecological networks. Pest spread is determined by the biophysical adjacency matrix, which is an asymmetric matrix of dispersal probabilities, with the values in rows indicating the probability of dispersal from the target node to all other nodes and the columns indicating the probability of dispersal to the target node from all other nodes (Fig. 1a). The spread of information is determined by the socioeconomic adjacency matrix, which can also be asymmetric (Fig. 1b).

INApest() treats bioentity spread differently from *INAscene()* by allowing explicit definition of separate short-distance (e.g. self-mediated) and long-distance (e.g. human-mediated) dispersal processes (Wichmann et al. 2009; Pautasso and Jeger 2014; James et al. 2015; Kelly et al. 2020). It is typical that short- and long-distance dispersal are mediated by different processes, for example, species traits versus human-mediated dispersal. When a separate long-distance dispersal matrix is provided, the two dispersal matrices are combined into a single matrix by treating short- and long-distance dispersal as separate binomial trials so that dispersal probability between nodes i and j is calculated as:

$$p_{ij} = 1 - (1 - SDD_{ij})(1 - LDD_{ij})$$

where SDD is short-distance dispersal probability and LDD is long-distance dispersal probability. Additional information on obtaining scenario parameters is provided in the Supplementary Material and code used to estimate parameters and implement scenarios is available in an online repository[1].

INApest() also permits explicit moderation of colonisation probability by environmental factors, such as climate and land use or land cover (an important consideration). This is achieved through multiplying the columns of the biophysical adjacency matrix (which contain the probability of dispersal to each node from all other nodes) by a vector of establishment probabilities. Establishment probabilities may be updated at each time-step, thus allowing changes in habitat suitability through time to be incorporated in simulating pest spread.

Another key departure of *INApest()* from the *INAscene()* function is that the spread of information (communication) through the network only occurs from

1 https://github.com/manaakiwhenua/SleeperPests/tree/main/Chilean%20needle%20grass.

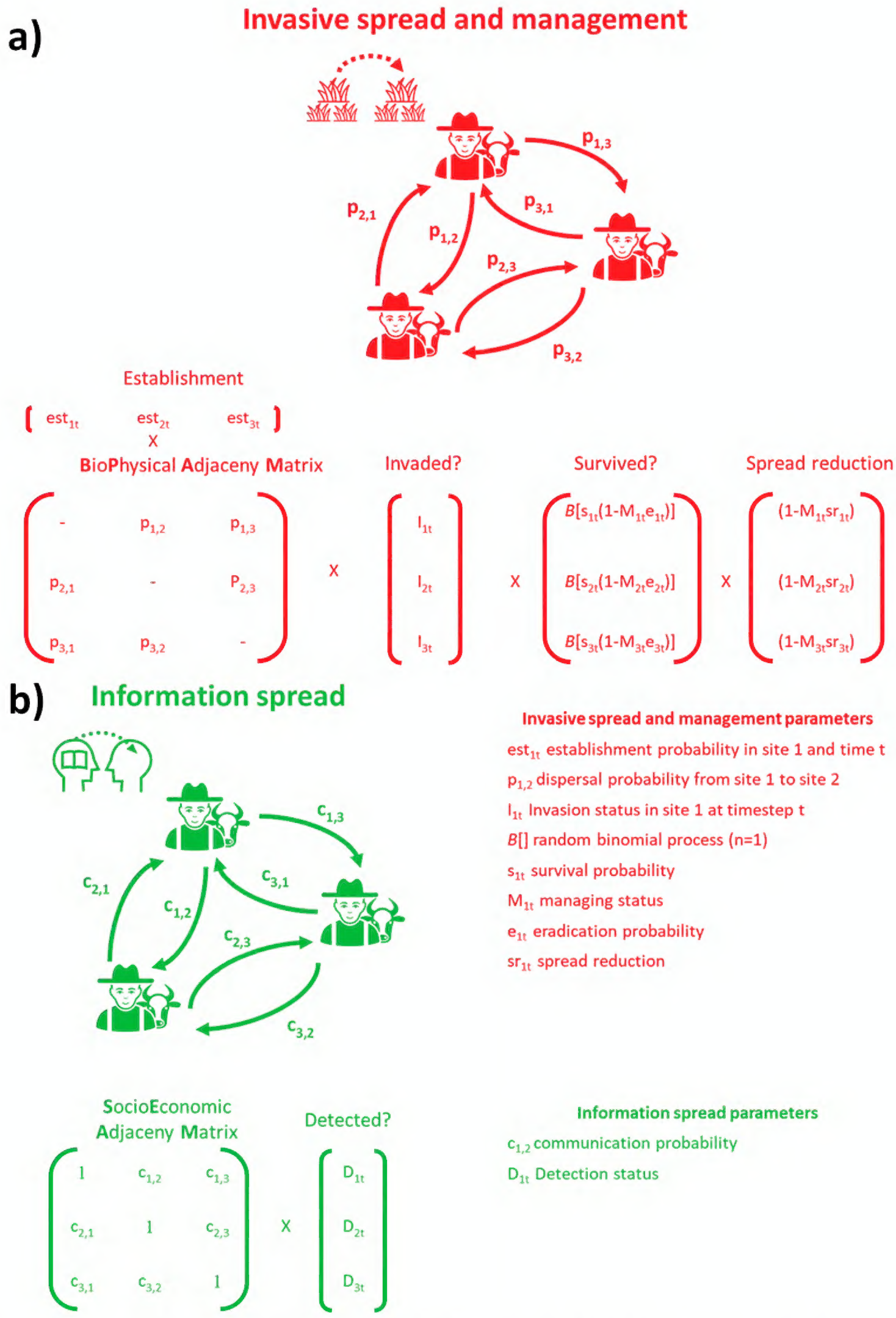

Figure 1. Schematic diagram indicating basic features of *INApest()*. Through a simple set of matrix operations habitat suitability, dispersal probability between sites, multiple management parameters and social network structure are integrated to permit simultaneous simulation of both pest (**a**) and information spread (**b**). Columns in the Biophysical Adjacency Matrix (BPAM) and Socioeconomic Adjacency Matrix (SEAM) are the probability, respectively, of being invaded or receiving information, rows are the probability of being a source of invasion or information. At each time-step, vectors store the invasion, information managing and detection status at each node (farm). Managing status is a binomial vector populated via a random binomial process contingent on information status and management adoption probability. In our study, we assumed a 1:1 relationship between nodes in SEAM and BPAM matrices, but a 1:many relationship would be possible (by setting communication probability = 1 between nodes under common ownership or management). Further details on the novel features of *INApest*() relative to *INAscene*() are provided in Table 1. The simulation process of *INApest()* and parameter settings for the scenarios are described in the text and supplemental information. Source code for the *INApest()* function and scripts used to produce results presented in this study as well as general tests of functionality are available at: https://github.com/manaakiwhenua/SleeperPests/tree/main/Chilean%20needle%20grass.

nodes with detected extant infestations. This is achieved through multiplying the rows of the socioeconomic adjacency matrix by a binary vector tracking the presence of detected extant infestations. This reflects the reality that agents (e.g. farmers) may only become receptive to information about a pest they know is present or nearby (e.g. neighbouring farm) and potentially or imminently threatening (Hester and Cacho 2017; Kaine and Wright 2022; Etherton et al. 2023). In simple terms, *INAscene()* simulates the spread of information about pest management technologies, while *INApest()* simulates spread of information about the threat of invasion. Provision of the socioeconomic adjacency matrix is not required to run *INApest()*. In such cases, there is assumed to be no spread of information between nodes.

INApest() permits a more nuanced approach to modelling invasive species management than *INAscene()* by explicitly separating the management response into detection, management adoption, spread reduction and eradication components. Detection probability is the probability of detecting the pest in each time-step. Management only occurs after detection of the pest or receipt of information from nodes with extant detected infestations. Zero management scenarios can be implemented simply by setting detection probability to zero in all nodes. Management adoption is the probability that management (eradication and spread reduction) is implemented on a given farm in a given time-step. Eradication probability is applied as a reduction to the annual survival rate of local populations when management is applied. Spread reduction is applied as a reduction in the dispersal probability from nodes when management is applied. When management is adopted, both eradication and spread reduction measures are implemented. Once a node obtains information it always potentially applies management, even once the pest has been eradicated from that node.

A key additional feature of *INApest()* is the ability to distribute initial infestations in proportion to the risk of invasion from external sources (e.g. proximity to an international port or airport) when an initial infestation vector is not provided and to incorporate ongoing invasion from external sources in simulating pest spread. Similarly, it is possible to select nodes which have information at the start of simulations (e.g. sentinel sites) and incorporate communication of information from external sources (e.g. biosecurity officers, consultants, media and social media) in simulating the spread of information through the network. Details of outputs from *INApest()* are provided in Supplementary Material.

Study system: Chilean needle grass invasion in NZ pastoral farms

We used *INApest()* to model the spread and management of the regionally restricted weed CNG which is established in limited areas in the Hawke's Bay, Marlborough and Canterbury regions of New Zealand (Connor et al. 1993). Under current climates in New Zealand, 15 million ha is climatically suitable, though much less than 1% is currently invaded and more area is expected to become suitable with climate change (Kriticos et al. 2004; Bourdôt et al. 2012, 2015). Establishment of CNG on dairy farms is largely prevented by intensive pasture management (high nutrient inputs and short return grazing intervals), wetter soils and competition from dense swards of ryegrass and clover (Bourdôt et al. 2015), so that it is justifiable to focus on modelling spread within the sheep and beef sector, rather than across all pastoral lands. Additional information on the impacts, status, reproduction and spread of CNG in New Zealand is provided in the Supplementary Material.

In New Zealand, invasive species management is often devolved to local government authorities once eradication is declared unfeasible. Consequently, invasive species management and investment decisions are often taken at the local government

(region) level. One consequence of this localised approach is that pest management planning often does not consider the benefits of control measures for reducing or preventing spread across administrative boundaries. This is the case for CNG where the cost of containing extensive infestations in the Hawke's Bay Region threatens political support for control measures within this region. Abandonment of control measures may increase the risk of spread to neighbouring regions where CNG is not present. This is especially concerning for the Manawatū-Whanganui region, where sheep and beef farming is a major contributor to the regional economy.

Simulation experiments

We chose a small set of simulation experiments to illustrate some of the questions that *INApest()* might address within the context of regional-scale CNG management responses (Table 2):

1. Validation: Considering historic infestation data, do our dispersal kernels produce realistic spread rates under a zero-management scenario?
2. Interaction between multiple management parameters under changing climates: Which management parameters and interactions between management parameters have the greatest influence on time-integrated metrics of CNG invasion and management response success under changing climates?
3. Cross border consequences of management decisions: How do management decisions in a CNG source region (Hawke's Bay) affect management outcomes in a neighbouring region (Manawatū-Whanganui)?
4. Interaction between communication, detection and climate change: How does communication with farmers about the threat of invasion affect invasive spread and management outcomes under current and future climates the Manawatū-Whanganui region?

Table 2. Summary of simulation experiments, their purpose and parameters varied.

Simulation experiment	Purpose	Parameters
Validation of invasive spread parameterisation against historic data	To test whether modelled invasive spread rates are similar to observed spread in available infestation time-series data	A single parameter set was used reflecting the best available understanding of invasion processes under current climatic conditions
Interaction between multiple management parameters under changing climates	Assess the relative influence of variation in individual management parameters and interactions between them on the rate and extent of invasion and on the probability of management success under current and future climates.	Multiple parameter combinations varying eradication and detection probability, spread reduction and communication probability under current and future climates (where climate moderates pest establishment probability) were used. The influence of management variables on invasive spread is documented in Fig. 1 and Table 1.
Cross border consequences of management decisions	Demonstrate the ability of *INApest()* to integrate dynamic external invasion threats and global change factors within multiple management scenarios by assessing the effect of management decisions in an infested region on invasive spread in a neighbouring currently non-infested region.	The key parameter varied is detection probability (assigned either 0 or 0.2) in the infested region. Detection probability = 0 is a zero-management scenario since information spread is dependent on detection and only farms with information can adopt management. Detection probability = 0.2 is a moderate management scenario. In the currently non-infested region detection probabilities ranging from 0 (no management) to 0.7 (intensive monitoring and management) were used. Simulations were performed under current and future climatic conditions.
Interaction between communication, detection and climate change	Demonstrate the ability of *INApest()* to integrate communication of the threat of invasion from known infestations on neighbouring farms and global change factors within multiple management scenarios.	Communication probability of either 0 (no communication) or 0.25 was assigned to pairs of farms within the critical distance (150 m) from each other within the currently non-infested region under invasive threat from the neighbouring infested region. In *INApest(),* communication permits pre-emptive management, since farms may receive information and, hence, adopt management, before being invaded. Detection probabilities ranging from 0 (no management) to 0.7 (intensive monitoring and management) were used. Simulations were performed under current and future climatic conditions.

Setting up the scenarios

At-risk locations (nodes) were defined as sheep and non-dairy (beef) cattle farms listed in the land-use database Agribase (Sanson 2000) with suitable climates for the establishment of CNG. Climatic suitability was estimated through the eco climatic niche model CLIMEX (Sutherst 1985) presented by Bourdôt et al. (2012) for present day (2020) climate and a future climate scenario –based on the moderate A1B climate scenario (IPCC 2000) for 2090 (i.e. balanced fossil–renewable growth, rapid globalisation, moderate population and medium emissions). The annual eradication probability parameter was set at 0.048 (based on the number of years taken to reduce the seedbank to < 1 seed per hectare with 95% confidence under management with glyphosate, Bourdôt (2010)). Distances (in metres) between farms were recorded as the minimum Euclidean distance between farm boundaries. Separate dispersal probabilities were estimated for short-distance (self-mediated) and long-distance (human-mediated) dispersal processes. Additional information on obtaining scenario parameters is provided in the Supplementary Material and code used to estimate parameters and implement scenarios is available in an online repository[2].

Information spread was simulated by permitting information transfer from farms with known (i.e. detected) extant CNG infestations to neighbouring farms within a critical distance of 150 m, which reflects the upper limit of natural annual spread for CNG (Bourdôt 2010). The probability of farms within the critical distance of known infestations receiving information (i.e. potentially implementing management) was defined by the 'communication probability' parameter. This represents the probability that farms at risk of invasion receive and absorb information about CNG monitoring and management from biosecurity officers or the likelihood that owners of at-risk farms will permit biosecurity officers to monitor for CNG on their farms. The socioeconomic adjacency matrix (which contains communication probabilities) was populated so that pairs of farms within the critical distance were assigned a fixed communication probability, while all other pairs of farms were assigned a probability of zero.

Validation against historic infestation data in the Marlborough region

The CNG implementation of *INApest()* was validated against historic spread data from an initial infestation in the Blind River area of Marlborough, north-eastern South Island, New Zealand. The initial infestation used in simulations was taken from infestation map of Bourdôt and Hurrell (1989). Three other historic data points were obtained from Bell (2006) who provided estimates of the number of pastoral properties infested in 2000 and 2005 and from Marlborough District Council in 2020.

Interactions between multiple management parameters under changing climates: Marlborough region

INApest() offers the potential to explore many (thousands or even tens of thousands) management scenarios. This can be useful when there is high uncertainty around parameter estimates, in assessing the relative impact of individual

2 https://github.com/manaakiwhenua/SleeperPests/tree/main/Chilean%20needle%20grass.

parameters (and interactions between them) on outcomes and to identify regions of parameter space likely to provide desired management outcomes. To explore this potential, we simulated CNG spread in the Marlborough region under current and future climates while varying multiple management parameters. In all scenarios, the management adoption probability parameter was set to 0.9, reflecting the high motivation of farmers to manage CNG infestations revealed by questionnaire studies (Suppl. material 1).

The other parameters varied and levels used were:

- communication probability (0, 0.025, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.5, 0.75) between neighbouring farms (< 150 m apart), otherwise 0;
- detectionprobability(0.025,0.05,0.075,0.1,0.15,0.2,0.25,0.3,0.4,0.5,0.75);
- eradication probability (0, 0.025, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.5, 0.75);
- pread reduction (0.05, 0.1, 0.3, 0.5, 0.9, 0.99, 0.999).

This gave a total of 7,700 parameter combinations for each climate scenario, for a total of 15,400 management scenarios. Each scenario was replicated across 30 simulations yielding a total of 462,000 simulations.

Invasive spread under each parameter combination and climate scenario was summarised as infested farm-years (expressed as a percentage of the maximum potential value). A value of 100 (maximum possible value) indicates that every farm was infested in every year of every realisation. We chose this time-integrative measure as it captures not only the total number of farms invaded, but also the rate at which the invasion spreads and the persistence of local infestations following invasion of farms. We also recorded management success as a binary variable using the restriction of infested farm-years to < 1% of the potential maximum farm-years value as our success criterion. This illustrates the potential for scenario analyses to reveal management strategies likely to achieve success against an objective success criterion.

To explore the relative effect of each management parameter and climate scenarios and interactions between them on invasive spread and management success, we fitted extreme gradient boosted regression trees of invasive spread and management success against management parameters and climate change scenario (Chen and Guestrin 2016). Visualisation of outcomes for selected combinations of detection and communication probability under each climate scenario was also used to assess combinations of eradication and spread reduction values required to achieve management success.

Cross-border consequences of management decisions

This simulation experiment demonstrates the potential of *INApest()* to integrate dynamic external invasion threats by exploring the impact of CNG management decisions in the Hawke's Bay region (which contains a widespread CNG infestation) on management outcomes in the currently non-infested Manawatū–Whanganui region under current and future (2090) climates. The two regions are independent political entities with the potential for decoupled biosecurity policy and strategy. The CNG invasion in Hawke's Bay is well entrenched and there is a real possibility that CNG control regulations could be abandoned there.

Two management scenarios were applied in the Hawke's Bay (detection probability of 0 or 0.2). Eradication probability was set at 0.049 (based on time taken to reduce the seedbank to < 1 seed per hectare, Bourdôt (2010)), spread reduction

at 0.999 (reflecting the combined effect of seed production prevention, exclusion of livestock during seeding periods, stringent hygiene measures and movement restrictions on hay from infested farms, Bourdôt (2010)), management probability at 0.9 (based on survey data presented in the Suppl. material 1) and communication probability (to farms < 150m from known extant infestations) at 0.25 (which is similar to rates of information transfer from sources other than first-hand experience in a previous study, Li et al. (2021)). Hawke's Bay simulation results were used to calculate invasion probabilities between individual Hawke's Bay and Manawatū–Whanganui farms. These were summarised to produce a matrix (farms x years) of annual cross-region invasion probabilities for Manawatū–Whanganui farms. These cross-region invasion matrices were supplied as the "InvasionRisk" parameter to the *INApest()* function call to simulate invasions in the Manawatū–Whanganui region. Invasions were initiated through a random binomial process using values in the first column of the cross-region invasion matrix and cross-region invasion probabilities were updated at each time step to reflect temporal changes in invasion risk from the Hawke's Bay region. In the Manawatū–Whanganui simulations, detection probability values from 0 to 0.7 were analysed. All other management parameters were identical to those used in the Hawke's Bay simulations. For each combination of detection probability and climate scenarios, 100 separate simulation runs were performed. Infested farm years were calculated for each simulation at each level of detection probability and time-series of invasions examined for a selected level of detection probability (0.05).

Interaction between communication, detection and climate change

This simulation experiment compared CNG invasive spread in the Manawatū–Whanganui region under scenarios with and without communication between farms about the threat of CNG invasion. In the scenarios including communication, information spread was permitted to farms within 150 m of known infestations and the annual communication probability parameter was set at 0.25. Cross-region invasion probabilities from Hawke's Bay to Manawatū-Whanganui farms (the InvasionRisk parameter in *INApest()* function calls) were derived from simulation in Hawke's Bay scenarios with detection probability = 0.2. All other management parameters were kept identical to those used in the previous simulation experiment. For each combination of detection probability and climate scenario, 100 separate simulation runs were performed. Infested farm years were estimated for each level of detection probability and time-series of invasions examined for a selected level of detection probability (0.05).

Results

Validation against historic invasion

Historic data points were well within the 95% confidence limits (across 100 separate runs) of the *INApest()* simulation results and similar to the median values (with a difference of three infested farms in 2000 and five for both 2005 and 2020, Fig. 2). According to the model, under current climatic conditions and zero management CNG would invade, on average, 170 farms after 80 years (roughly 2065) in the Marlborough region, with the upper bound of the 95% confidence interval

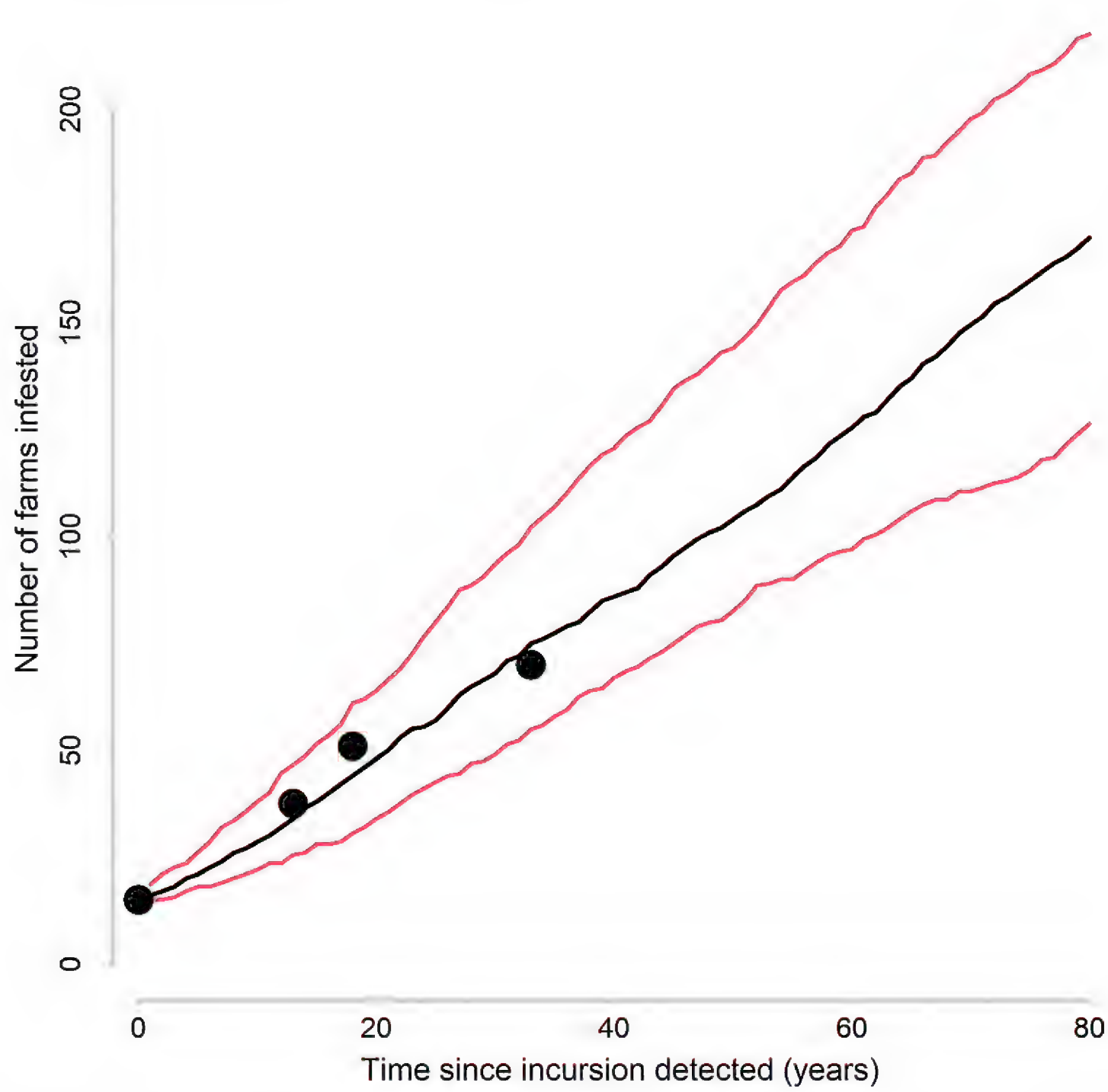

Figure 2. Median (black line) and 95% confidence limits (red lines) of number of nodes (i.e. sheep and beef farms) in the Marlborough region of New Zealand invaded by Chilean needle grass in *INApest()* simulations under current climatic conditions, with no management (i.e. detection prob. = 0) and with initially infested farms derived from Bourdôt and Hurrell (1989). Black filled circles are data points derived from Bell (2006) and the most recent (2020) comprehensive infestation dataset available (https://data-marlborough.opendata.arcgis.com/datasets/b2ca1834feb94b658ae5118289044e71_10/explore).

being 217 infested farms. The increase in infested farms was linear, indicating the invasion did not approach an asymptote within the simulation period.

Varying management parameters under changing climates: Marlborough region

Detection probability and eradication probability had by far the strongest influence both on invasion rates (infested farm years, expressed as a percentage of maximum potential value) and management success (probability of limiting invasion to < 1% of maximum potential infested farm years) in XGBoost models (Table 3). Spread reduction and communication had a moderate influence with climate scenario being the least influential predictor. This indicates that, considering a very broad range of potential management parameters, efforts aimed at increasing detection probability and eradication are likely to provide the largest benefits in reducing CNG infestation rates in Marlborough.

The largest interaction effect for infestation rates was between eradication probability and spread reduction (Fig. 3a). Increases in spread reduction greatly reduced invasion rates when eradication probability was less than 0.2, while eradication had a strong effect on invasion rates at all levels of spread reduction. There was a sizeable interaction between climate scenario and detection probability, with invasion rates being around 50% higher under the future (2090) climate scenario

Table 3. Relative influence of management variables and climate scenarios on Chilean needle grass-infested farm years and probability of management success (infested farm years < 1% of the maximum potential value) in cross-validated XGBoost regression trees. Gain is the reduction in unexplained variance each time a predictor is used to make a new branch; Frequency is the proportion of times a predictor is used to make a new branch and Coverage is the proportion of observations involved in branches using the predictor. Values are means and 95% confidence intervals across 10 separate fold models, where different portions of the dataset are withheld for validation.

Infested farm years						
Predictor	Gain	95% CI	Frequency	95% CI	Coverage	95% CI
Eradication	0.40	0.08	0.38	0.03	0.39	0.09
Detection	0.38	0.08	0.37	0.04	0.41	0.10
Spread reduction	0.11	0.04	0.09	0.04	0.10	0.05
Communication	0.09	0.04	0.13	0.04	0.08	0.02
Climate	0.03	0.02	0.03	0.03	0.02	< 0.01
Success probability						
Predictor	Gain	95% CI	Frequency	95% CI	Coverage	95% CI
Eradication	0.46	< 0.01	0.28	< 0.01	0.32	< 0.01
Detection	0.35	< 0.01	0.28	< 0.01	0.27	< 0.01
Communication	0.09	< 0.01	0.23	< 0.01	0.19	< 0.01
Spread reduction	0.09	< 0.01	0.17	< 0.01	0.16	< 0.01
Climate	0.01	< 0.01	0.05	< 0.01	0.06	< 0.01

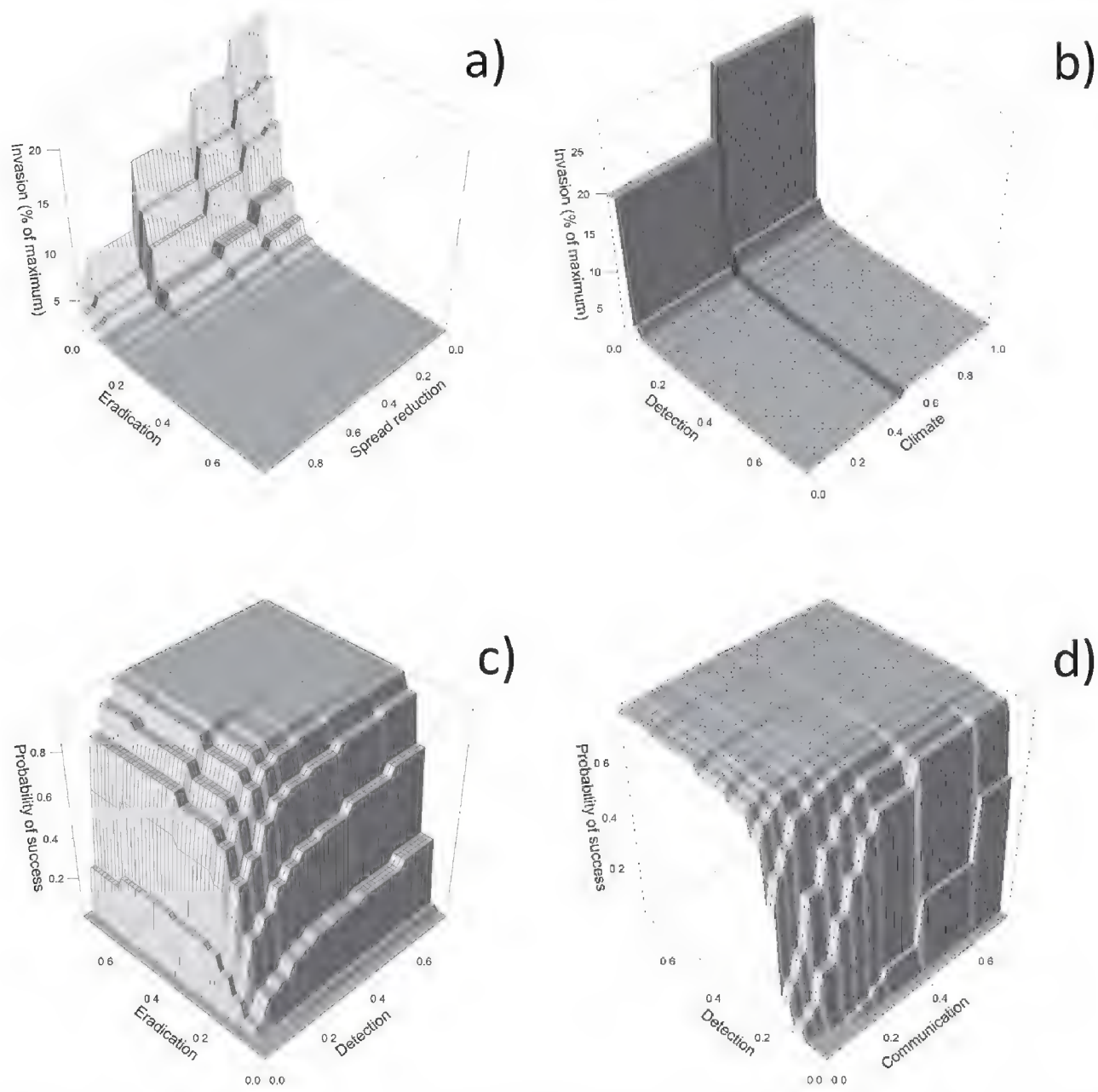

Figure 3. Perspective plot of interactions between predictor variables within the XGBoost models fitting variation in Chilean needle grass invasion rates (**a, b**) and management success (**c, d**) to management parameters and climate. **a.** Increases in spread reduction greatly reduced invasion rates when eradication probability was less than 0.2, while eradication has a strong effect on invasion rates at all levels of spread reductions; **b.** Invasion rates were about 10% higher under the 2090 climate scenario at the lowest levels of detection probability; **c.** Scenarios where both eradication and detection probability were greater than 0.25 gave the highest probability of success; **d.** At the lowest levels of detection invasion rates were 50% higher under the future climate scenario.

at the lowest levels of detection, while, at higher levels of detection, the effect of climate was minimal (Fig. 3b).

The largest interaction effect for management success was between eradication and detection, with scenarios where both eradication and detection probability were greater than 0.25 giving the highest probability of success (Fig. 3c). There was also a sizeable interaction between detection probability and communication probability, with increases in communication greatly enhancing success probability when detection was less than 0.2 (Fig. 3d).

Fig. 4 presents contour plots of CNG invasion rates (infested farm years, expressed as a percentage of maximum potential value) with respect to eradication probability and spread reduction for selected combinations of detection and communication probability under current and future climates. Irrespective of climate, no combination of eradication and spread reduction reduces invasion below the 1% containment threshold with zero communication and low detection probability (i.e. there are no aquamarine areas on contour plots, Fig. 4a, e). Despite this, the invasion rate is much higher under future climate for this combination of detection and communication (i.e. more red, orange and yellow areas). Under both climate scenarios, increasing communication at the lower level of detection greatly decreases invasion rates, but does not aid in restricting invasions below the 1% containment threshold (compare Fig. 4a, c, e, g, respectively). At high levels of detection under both climate scenarios (Fig. 4b, d, f, h), the contour demarcating the < 1% success criterion indicates that the eradication probability required to achieve success declines linearly with increasing spread reduction. This shows that the effectiveness of eradication methods required for success may be reduced if more stringent movement restrictions and hygiene measures are implemented. Finally, the addition of communication at high detection rates causes a ~ 25% reduction in the eradication rate required to achieve success under current climates across all levels of spread reduction and a ~ 30–50% reduction under future climates (compare Fig. 4b, d, f, h, respectively).

Cross-border consequences of management decisions

Implementing control of CNG populations in the source region (Hawke's Bay) greatly reduced the mean number of invasion events in the neighbouring currently non-infested region (Manawatū-Whanganui) under both climate scenarios (Fig. 5a, b). Under the zero-management scenario in the source region, the number of invasion events increased with time to just under 15 per year under current climate and 40 per year under future climate. At the end of the simulation period (80 years), almost all farms in the currently non-infested region had a less than 1 in 100, 000 annual chance of invasion from the source region under current climate and with management of populations in the source region (Fig. 5c). Meanwhile, under future climates, most farms in the eastern portion of the currently non-infested region (i.e. closest to the source region) had at least a 1 in 10, 000 annual chance of invasion (Fig. 5d). With zero management of source populations and under the current climate, almost the entire currently non-infested region had at least a 1 in 1000 annual chance of invasion (Fig. 5e). Similarly, under zero management at the source and under the future climate scenario, many farms in the eastern portion of the currently non-infested region have at least a 1 in 100 annual chance of invasion (Fig. 5f).

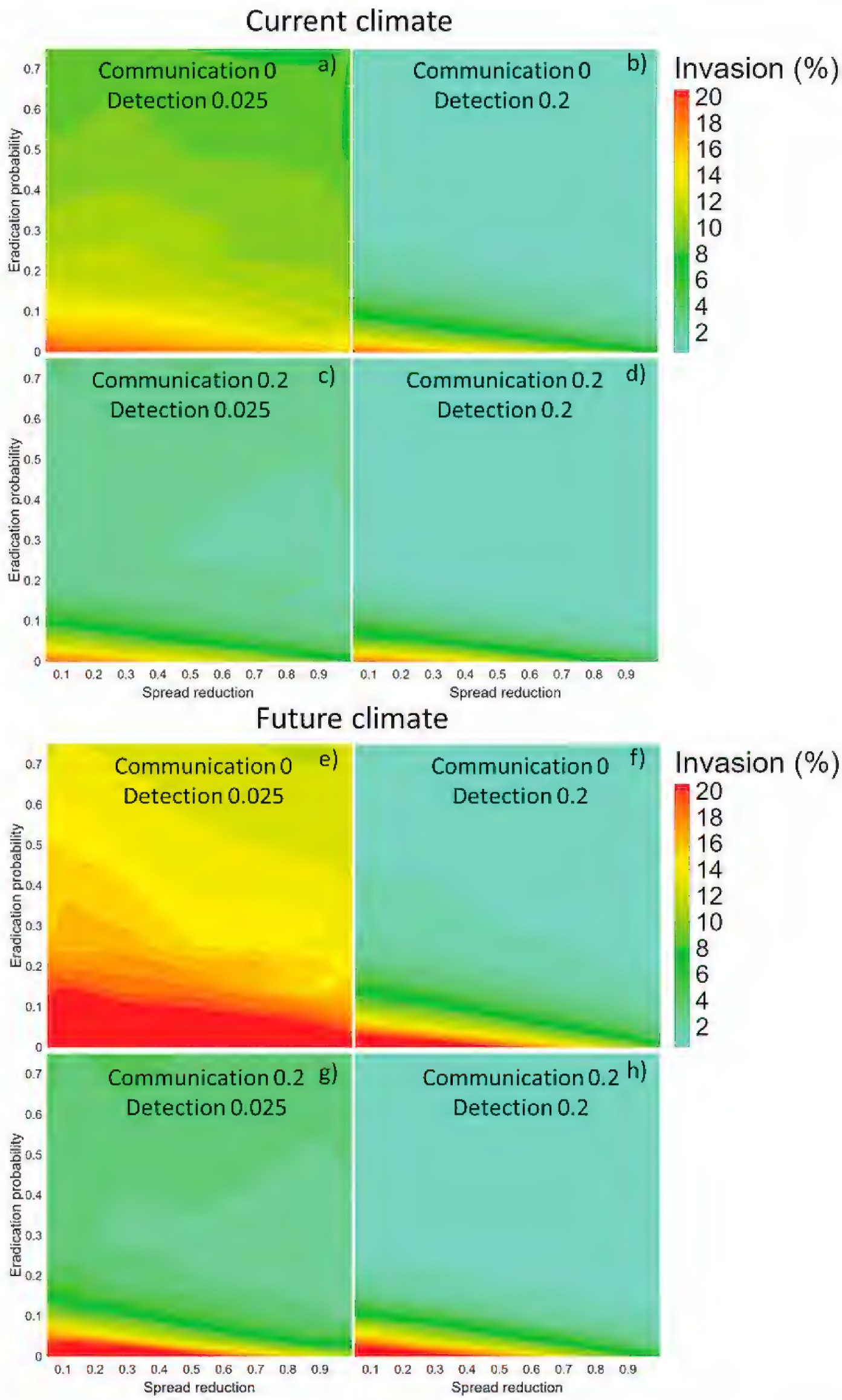

Figure 4. Contour plots of mean (across simulations) Chilean needle grass-infested farm years (expressed as a percentage of the maximum possible – all farms infested in every year of each simulation) from Chilean needle grass *INApest()* simulations in the Marlborough region under *current* (**a–d**) and *future* (**e–h**) climatic conditions. Areas covered by the lightest aquamarine shade indicate management success following the criterion that infested farm years are less than 1% of potential maximum. Each panel shows results for each combination of eradication probability and spread reduction given different levels of annual farm-level detection probability ("Detection") and annual communication probability to farms neighbouring known infestations ("Communication"). Spread reduction measures could relate to possible movement restrictions or hygiene strategies that reduce the likelihood of a farm exporting propagules. Given the seed bank longevity, an eradication probability of 0.05 is considered realistic.

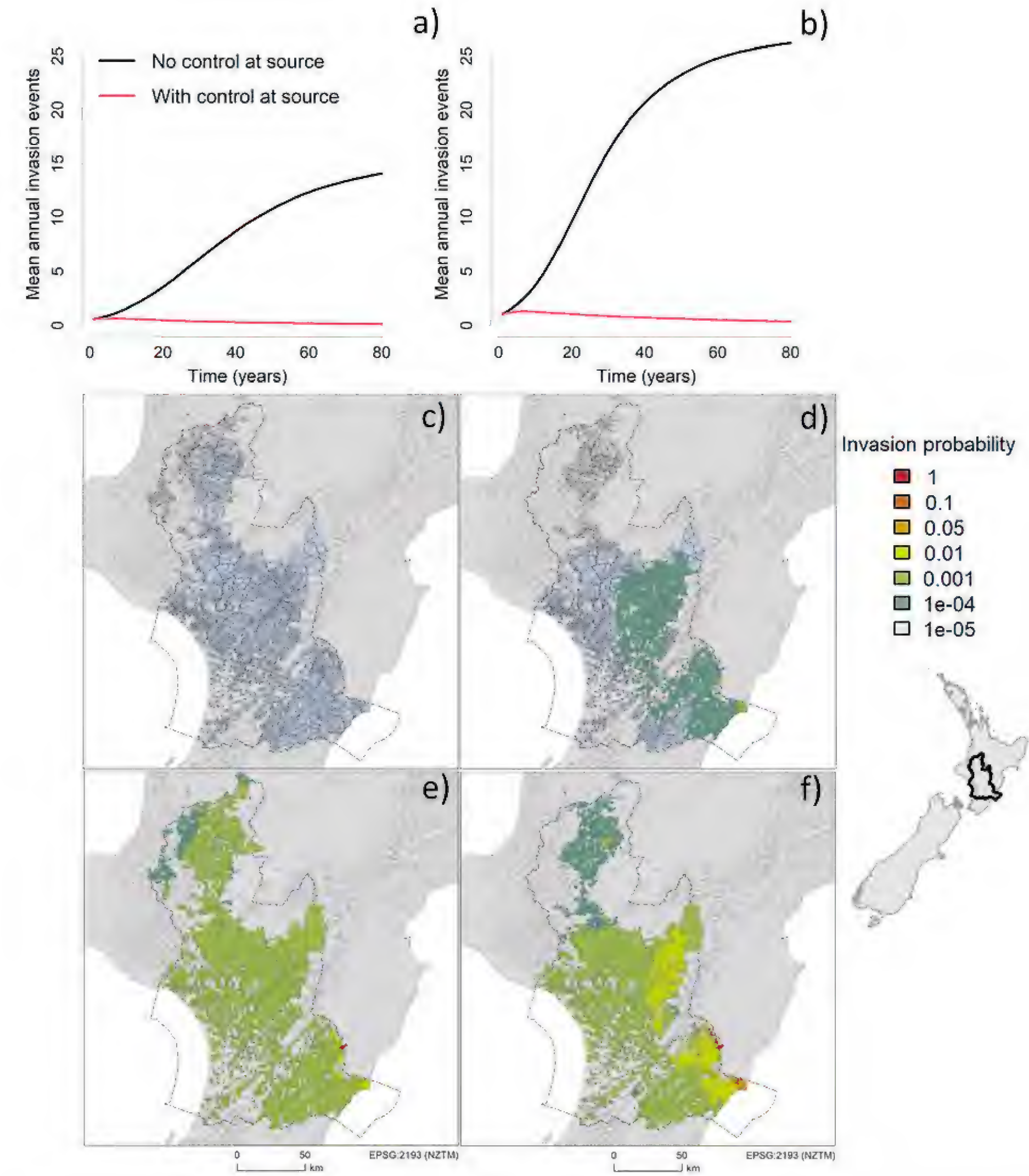

Figure 5. Time-series of mean annual external invasion events in the currently non-infested Manawatū-Whanganui region of New Zealand from source populations of Chilean needle grass in the Hawke's Bay region under current (**a**) and future (**b**) climate and maps of annual external invasion probability for individual farms in the currently non-infested region at the end of the simulation period (**c–f**). Red and black lines in **a** and **b** indicate, respectively, results from scenarios where management either is ("With control at source", detection probability = 0.2) or is not ("No control at source", detection probability = 0) applied to infested farms in the source region. Invasion heat maps at the end of the simulation period under current climate for the "With control at source" and "No control at source" scenarios are presented in **c** and **e**, respectively. Corresponding maps for future climate are presented in **d** and **f**.

Absence of management in the source region greatly reduced management efficacy (i.e. caused higher infestation rates) in the currently non-infested region at all levels of detection probability and this effect is exacerbated under future climatic

conditions (Fig. 6); here, results are expressed in terms of farm-years infested – a time integrative measure of impact. Absence of management causes an excess of between 12,000 and 25,000 (3.5% to 7.3% of the maximum potential value) infested farm years under current climate (for non-zero detection probabilities) and an excess of 25,000 to 30,000 (7.7% to 9.2% of the maximum potential value) under future climate. This demonstrates that, even under intensive management regimes (high detection probability) in the currently non-infested region, lack of management in the source region leads to higher rates of infestation in the neighbouring (currently non-infested) region.

Results for a single level of detection probability (0.05) in Manawatū-Whanganui reveal how the impacts of management decisions in Hawke's Bay develop over time (Fig. 7a, b) with respect to the number of farms infested. Under both climate scenarios, the absence of management in Hawke's Bay leads to the number of infested farms reaching a persistently high plateau relative to scenarios where CNG control is implemented in Hawke's Bay. By the end of the simulation period (80 years), absence of management in the Hawke's Bay produced an excess of around 500 farms infested annually under current climate and around 700 under future climate (respectively, 11.7% and 17.2% of at-risk farms). Maps of individual farm-level invasion probability (i.e. proportion of simulations in which a farm is infested at a given time-step) in Manawatū-Whanganui at the end of the simulation period under current climate (Fig. 7c, e) reveal a region-wide increase in invasion rates in the absence of CNG management in the Hawke's Bay region, relative to adoption of control in Hawke's Bay. There was evidence of very high (> 0.7, i.e. infested in > 70% of simulations) infestation probability in farms bordering Hawke's Bay (on the south-eastern edge, Fig. 7e) and throughout most of Manawatū-Whanganui region farm-level invasion probability increased to between 0.1 and 0.3 (i.e. farms were infested in

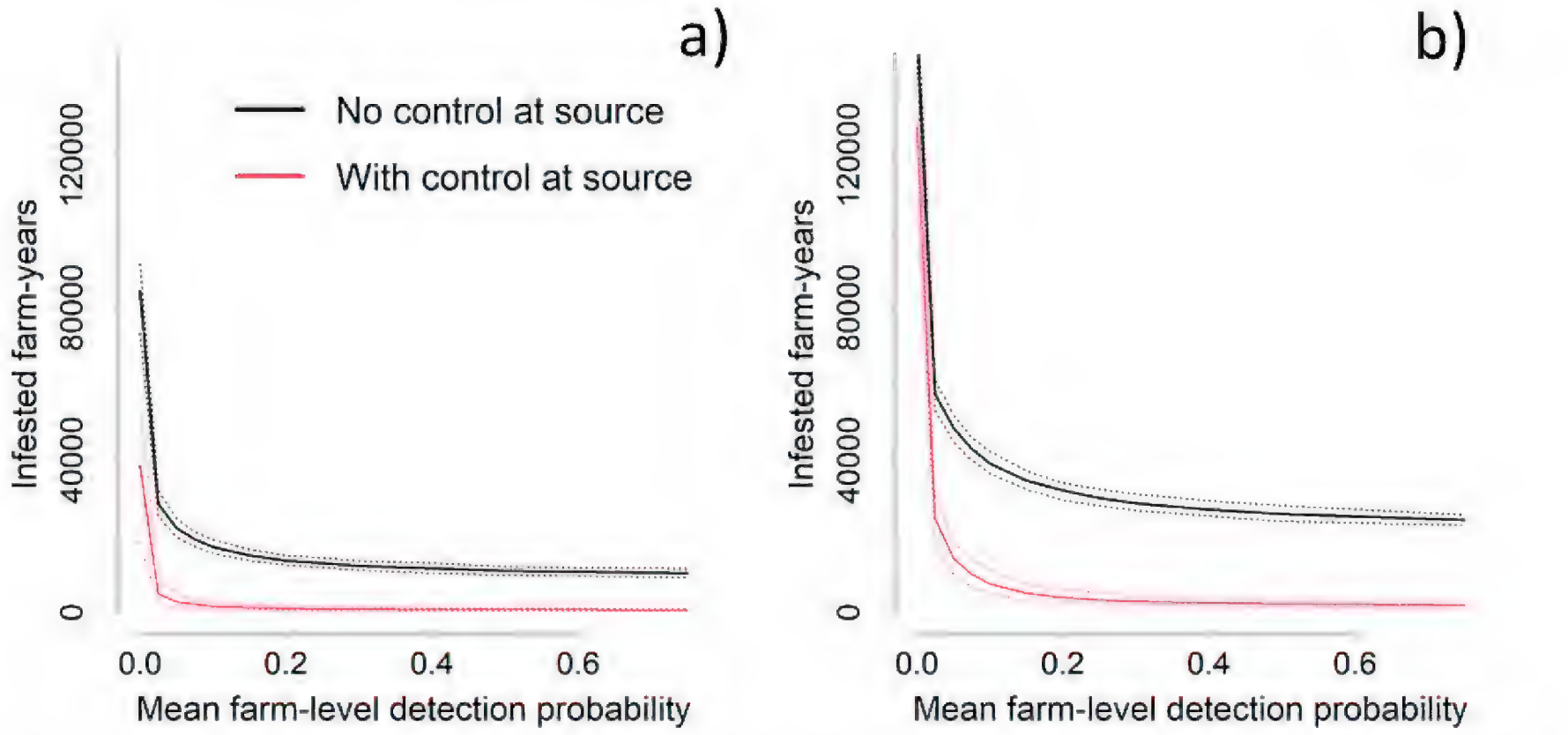

Figure 6. Infested farm years (the mean sum of infested farms across all years of individual simulation runs), under current (**a**) and future climatic conditions (**b**) in Chilean needle grass *INApest()* simulations with differing farm-level mean annual detection probabilities for the Manawatū–Whanganui region of New Zealand under current and future climate. Initial invasions were derived through random selection weighted by invasion probability from infested farms (as of 2021) in the Hawke's Bay region and simulations incorporated ongoing invasion derived from *INApest()* simulations in the Hawke's Bay region where management either is ("With control at source", detection probability = 0.2, red lines) or is not ("No control at source", detection probability = 0, black lines) applied to infested farms in the source region. Solid lines indicate median values and dashed lines indicate 95% confidence bounds (across individual simulation runs).

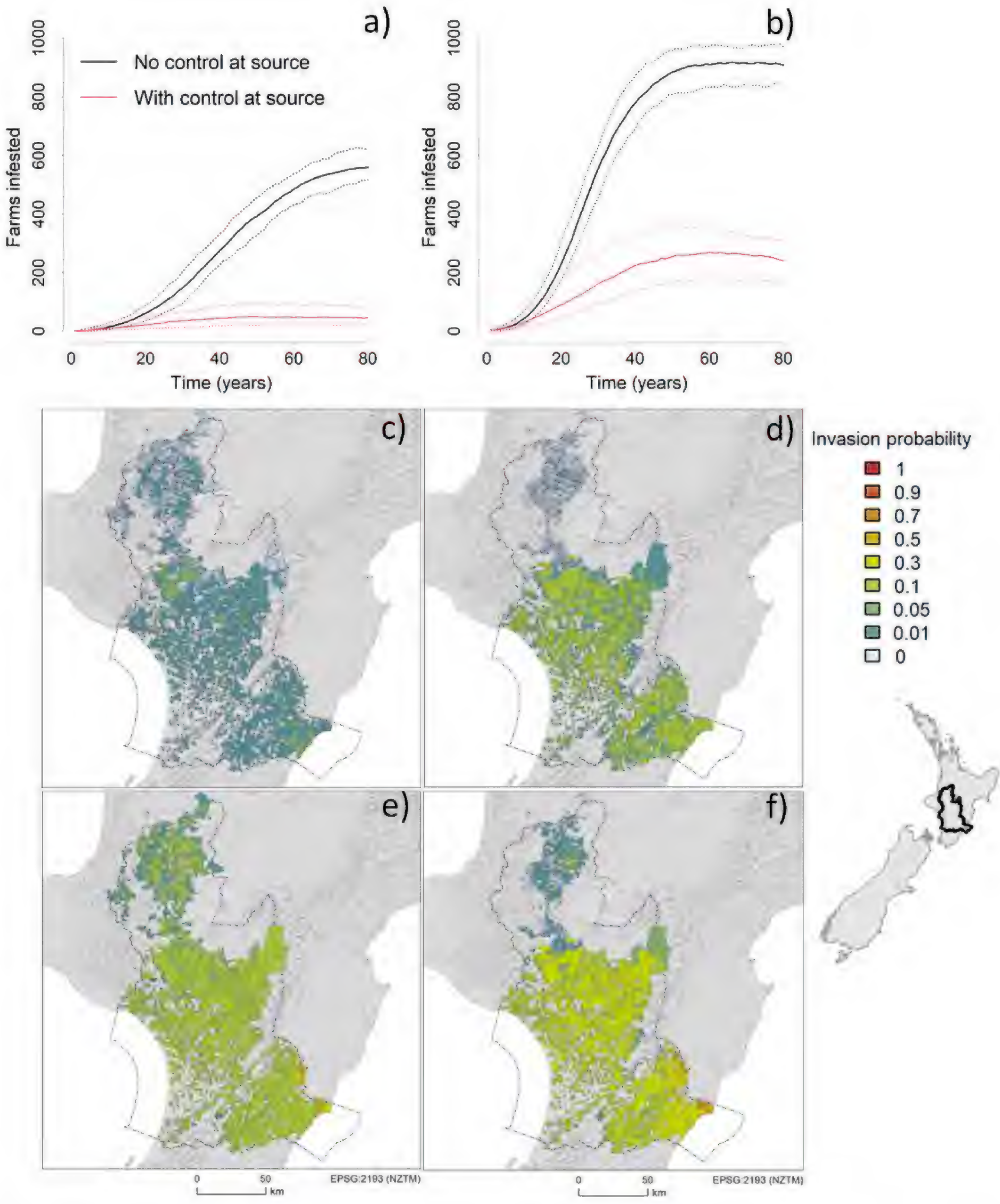

Figure 7. Time-series of Chilean needle grass-infested farms under a moderate management scenario (annual farm-level detection probability = 0.05) during invasion simulations in the currently non-infested Manawatū-Whanganui region incorporating invasion risk from source populations in the Hawke's Bay region under current (**a**) and future (**b**) climate and maps of individual farm invasion probability (proportion of simulations in which a farm is infested) at the end of the simulation period (**c–f**). Red and black lines in **a** and **b** indicate, respectively, results from scenarios where management either is ("With control at source", detection probability = 0.2) or is not ("No control at source", detection probability = 0) applied to infested farms in the source region (Hawke's Bay). Solid lines indicate median values and dashed lines indicate 95% confidence bounds (across individual simulation runs). Invasion heat maps at the end of the simulation period under current climate for the "With control at source" and "No control at source" scenarios are presented in **c** and **e**, respectively. Corresponding maps for future climate are presented in **d** and **f**.

10–30% of simulations). The spatial pattern of results was very similar under future climate (Fig. 7d, f), the main difference being that invasion probability was between 0.3 and 0.5 for most farms in the absence of management in Hawke's Bay. The maps also indicate reduced invasion probability under future climate in the extreme north of Manawatū-Whanganui (compare Fig. 7c, d, e, f, respectively), indicating that future climates may be less favourable to CNG invasion in this area.

Interaction between communication, detection and climate change

Fig. 8 illustrates how climate change, communication and detection probability interact. Results from simulations in the Manawatū–Whanganui region for hypothetical invasions from the Hawke's Bay show that, at low-to-moderate levels of detection probability the addition of communication between neighbouring farms reduces CNG infestation rates (Fig. 8a, b). This effect is much more apparent under future climatic conditions (compare Fig. 8, b). Results for a single level of detection probability (0.05) emphasise the increased benefit of between-farm communication under future climatic conditions (compare Fig. 8c, d). Adding between-farm communication results in 250 fewer farms being infested annually by the end of the simulation period under current climate and 1,500 fewer farms infested under future climate (respectively, 5.9% and 36.9% of at-risk farms). Maps of individual farm invasion probability at the end of the simulation period reveal that, when communication between neighbouring farms occurs under current climatic conditions, most farms are very unlikely to be infested (invasion probability < 0.05, Fig. 8e). By contrast, in the absence of between-farm communication and under future climatic conditions, most farms are very likely to be infested by CNG (invasion probability > 0.7, see the dark orange- and red-shaded areas in the Fig. 8h). These results indicate that enhancing communication between farms will be increasingly important in limiting the spread and impacts of future CNG incursions in the Manawatū–Whanganui region under future climates.

Discussion

In this study, we present a method for pest management scenario analysis using simple matrix operations to integrate global change and social factors into models of pest spread and management. This method successfully reproduces historic invasion patterns and enables the exploration of numerous parameter combinations. These simulations demonstrate the potential for this method to reveal which variables most strongly reduce pest spread and enhance management success. Additionally, they help identify the effect of interactions between variables and the parameter combinations that maximise the success of management responses.

Our simulations also demonstrate the potential for our novel method to permit the design of targeted experiments to address specific issues, such as the impact of local management decisions on invasions across political boundaries and how improved communication within social networks might enhance pest management outcomes. While the experiments in this study cover only a small subset of possible questions, they demonstrate the potential of these simple, but flexible, simulation tools.

In the following sections, we discuss the broader implications of our results for using simulation-based scenario analyses in pest management planning and prioritisation. We also highlight key functionalities of our proposed tools that were not explored in the current experiments.

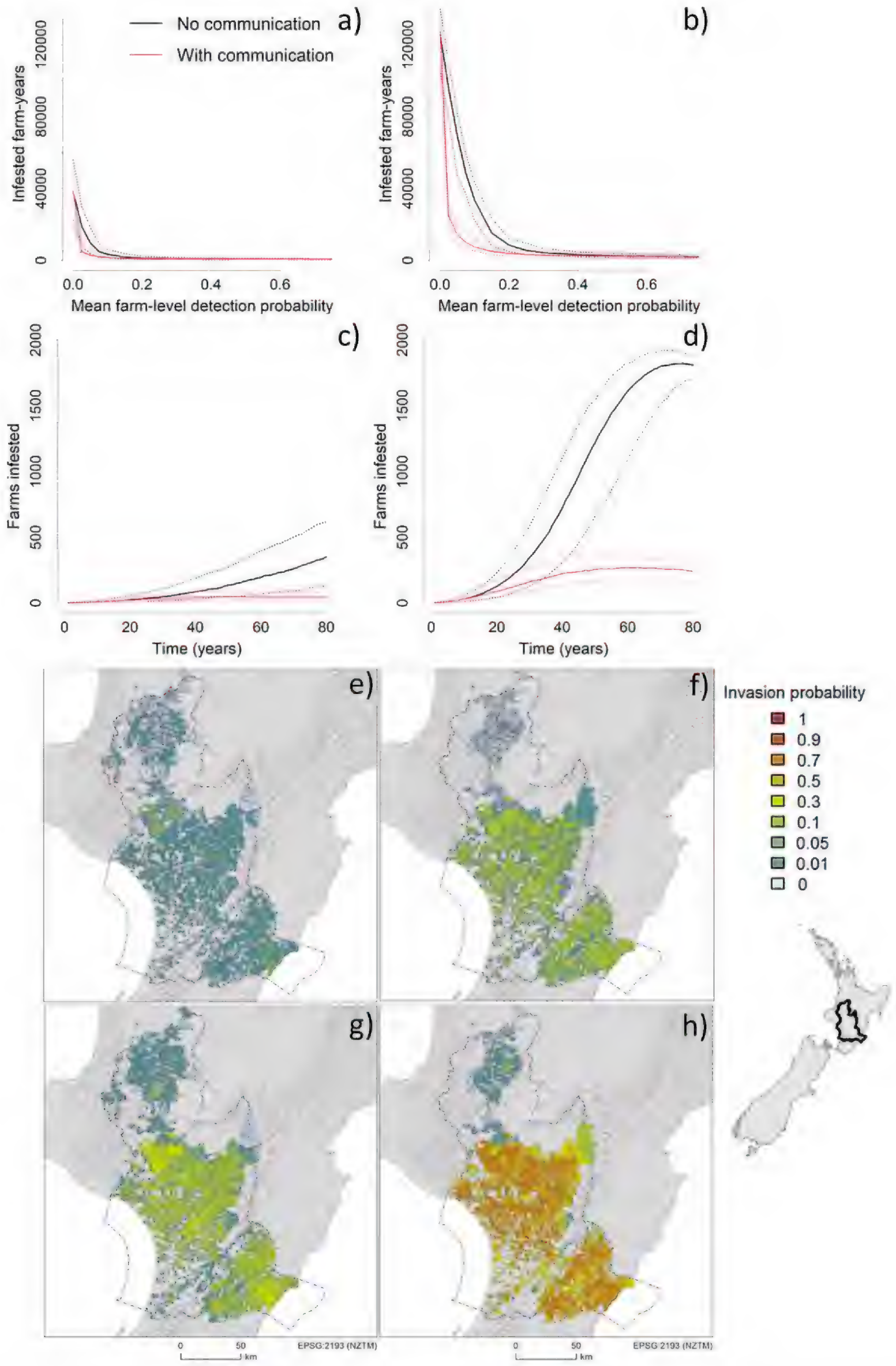

Figure 8. Chilean needle grass-infested farm years (the mean sum of infested farms across all years across individual simulation runs) for multiple mean farm-level detection probabilities under current (**a**) and future (**b**) climates for the Manawatū-Whanganui region. Red and black lines indicate, respectively, results from scenarios where farms near known infestations either are or are not warned by of potential invasion ('With communication' or 'No communication'). Time series of infested farms for a single level of detection probability level (0.05) under current (**c**) and future (**d**) climates for either communication scenario and maps of Chilean needle grass invasion probability (across separate simulation runs) of individual farms after 80 years where farms near known infestations either are (**e, f**) or are not (**g, h**) warned of potential invasion and under current (**e, g**) and future (**f, h**) climatic conditions.

Matrix-driven simulation models for multidimensional pest scenario exploration

We analysed over 15,000 scenarios of CNG invasion in the Marlborough region, examining the effects of management effectiveness (detection, eradication and spread reduction), social factors (management adoption and information dissemination), climate change and their interactions on invasive spread and management success. While previous studies (Jeger et al. 2007; Pautasso et al. 2010b; Buddenhagen et al. 2017; Andersen et al. 2019; Garrett 2021) have shown the potential of simulation-based scenario methods for exploring pest management, our study is the first to integrate global change, social factors and multiple management parameters into pest management outcomes using simple matrix-driven simulation models. Our new method, combined with flexible statistical tools like gradient boosted regression trees, offers unprecedented predictive power for understanding how interactions between various factors can influence pest management outcomes. A key strength of this approach is its ability to identify the specific combinations of management parameters that are most likely to lead to success. By revealing how the likelihood of success varies across the full range of factors that biosecurity planners must consider, this method can help overcome the barriers to using objective scenario analyses in pest response prioritisation and planning.

Cross-border consequences of management actions

Improving coordination between jurisdictions has been highlighted as a key strategy to mitigate the spread and impacts of pests (Pluess et al. 2012; IPBES 2023), particularly in the wake of climate change and pest range shifts (Walther et al. 2009). This includes more cohesive regional, national and international policy and regulations and developing risk assessments that include the effect of policy, the public and relevant industries on pest spread (IPBES 2023; Maher et al. 2024). However, cross-border considerations and coordination are often lacking in weed risk assessments (Beaury et al. 2021; Maher et al. 2024) resulting in disjointed efforts in monitoring and controlling problematic weeds and identifying their impacts on neighbouring regions (Bourdôt and Buddenhagen 2023). For CNG invasions, *INApest()* simulations revealed a hundredfold increase in the annual chance of a farm in the non-infested Manawatu-Whanganui region being invaded by CNG when no management is enacted in the infested Hawke's Bay, under both current and future climate scenarios. This highlights the potential for *INApest()* to reveal the impacts of poor coordination in pest management across jurisdictions.

INApest() has potential applications for strengthening cross-border weed management. At a regional or national scale, *INApest()* can be incorporated into planning of border and early post-border responses for changing trade patterns, such as increases in the number of imported and exported products and resources and changes in import source countries and regions. This is particularly relevant for managing and monitoring pests and their dispersal pathways, as escape from horticulture and agriculture are amongst the most important pathways contributing to pest introductions (Buddenhagen et al. 2021; McGrannachan et al. 2021). At a local level, the network simulation model can be incorporated with decision-support tools to advise farmers of the management implications and solutions for pest infestations and the risk these infestations impose on their own and neighbouring

properties (Bagavathiannan et al. 2020). This could be particularly beneficial for farm properties that border other regional jurisdictions with different weed regulations, to help raise awareness and foster cross-border management action with neighbouring farm owners. Increasing frequency and intensity of major disturbance events such as flooding predicted with climate change (Ministry for the Environment 2018; Bodeker et al. 2022) has the capacity to increase the risk of cross-border weed infestations. *INApest()* could be useful in predicting the risk of cross-border weed spread from such disturbance events under different management scenarios, as has been shown with flooding events during Cyclone Gabrielle in Hawke's Bay (Buddenhagen et al. 2024).

Benefits of improved communication

Model simulations using *INApest()* have demonstrated the potential importance of information dissemination between neighbouring properties in reducing pest spread, particularly under the threat of future climate change. In our simulation experiment, we found that communication of the threat of invasion prevented as many as 37% of at-risk farms from being invaded relative to a scenario where communication was absent. This is a very strong effect. In *INApest(),* communication of the threat of invasion increases pre-emptive management adoption by landowners neighbouring known infestations. Pre-emptive communication is critical to the success of pest management responses by increasing early detection and eradication of new infestations and reducing spread from existing infestations, hence reducing medium-to-long term control costs (Epanchin-Niell and Hastings 2010; Diagne et al. 2021) and impacts on production of affected industries (Saunders et al. 2017). Our simulation results, along with existing literature, emphasise the importance of including pre-emptive communication that improve detection and management adoption in pest management response success.

Enhanced communication between landowners can benefit pest management outcomes via other processes, such as increased preparedness and capacity of neighbouring landowners to deal with new and spreading infestations, including through increased cooperation and coordination of control efforts or through the sharing of control costs (Gass et al. 2010). Enhanced communication between landowners may also promote the socialisation of best management practices (Wilson et al. 2009). However, communication may also influence some landowners to adopt less expensive and less effective practices in hopes of reducing overall costs. This was illustrated in a study using an impact network analysis that incorporated managers' abilities to evaluate the economic outcomes of their neighbours (Etherton et al. 2023). Lastly, sustained communication between landowners builds trust and cohesion within communities, leading to better cooperation, coordination and outcomes when responding to current (Schelhas et al. 2021) and possibly future pest threats.

Parameterisation and validation

For many invasions, particularly involving species that have recently established in a country or region, it may be challenging to find parameter estimates in the published literature. Regarding invasion probability, species specific information on climate and habitat suitability may often be available from published literature, with frameworks such as CLIMEX (Kriticos et al. 2015) greatly increasing the

availability of climate-based distribution models and simplifying the development of new models. These models can be used to sale establishment and survival probabilities. Natural dispersal distance may be estimated from basic traits (e.g. Tamme et al. (2014)), application of generic dispersal kernels (Nathan et al. 2012) or mechanistic models relating to specific vectors (e.g. Will and Tackenberg (2008); Nathan et al. (2011)). Network analysis of maps of pest habitat can provide a proxy for dispersal networks through landscapes (Tischendorf and Fahrig 2000; Urban and Keitt 2001; Plex Sulá et al. 2025). Human aided dispersal can be scaled according to data on known pathways like livestock (Mason et al. 2021) or vehicle movements (Carlin et al. 2025) or generic models of human visitation (Schläpfer et al. 2021).

For many species, mortality data for different control methods may often be available and can be used to calibrate local population eradication, as we have done in this study. For well-studied species, the efficacy of measures designed to reduce human-mediated dispersal may often be known (e.g. Liew et al. (2023)) and reviews of effectiveness for a wide range of such measures are available (e.g. van Klinken et al. (2023)). It is possible to gain estimates of management adoption probability through surveys or questionnaires (Suppl. material 1, Kaine and Wright (2022)) and existing data on potential impacts (e.g. threat to economic enterprises, human or animal health) of invasive species could be used as a proxy management adoption. Expert knowledge elicitation has potential for providing parameter estimates for cases where experts have extensive experience with specific pests in relevant systems (Hughes and Madden 2002; Etherton et al. 2025; Fontan et al. 2025; Robledo et al. 2025). Buddenhagen et al. (2017) provide an example of how data on information spread within socioeconomic networks can be gathered. It may be impracticable to do this for every new incursion, but multiple pests may share similar socioeconomic networks, so that general information about information sharing within networks could be used to scale the spread of information when species-specific information is unavailable.

Complex simulation models may involve a high degree of uncertainty in parameter settings on models of key processes and validation should be undertaken wherever possible (DiRenzo et al. 2023). However, as we found in our study, it may be difficult to source detailed time-series of reliable infestation data against which to validate modelled invasive spread (Parry et al. 2013). Use of incomplete or biased infestation data in validation could produce misleading conclusions regards model accuracy. One advantage of scenario analyses is that assumptions must be explicitly stated, which facilitates critical evaluation of model outputs in the absence of reliable validation data (e.g. Parry et al. (2013); DiRenzo et al. (2023)). They also provide potential for sensitivity analyses (similar to our Figs 3, 4, Table 3) which can reveal parameters exercising the greatest influence over invasive spread and, thus, help to prioritise efforts to improve parameter estimates (i.e. parameter uncertainty *sensu* Saffer et al. (2025)). Finally, scenario models may provide an indication of inherent uncertainty by recording the variation in outcomes across individual simulation runs for a single combination of parameter values (i.e. process uncertainty *sensu* Saffer et al. (2025)).

Unexplored potential of matrix-based simulation methods

The generalised simulation processes and flexibility in input parameter definition provided by simulation methods such as *INApest()* offer a much broader range of scenario analyses than can be demonstrated in a single study. Unexplored

functionality includes the ability to: incorporate spatiotemporal variation in habitat suitability, management parameters and pest invasive biology; include different node types (e.g. livestock sale yards and pastoral farms in the context of CNG spread by livestock transport) in socioecological networks; examine the effect of social network structure on the spread of information about pest threats; compare strategies for increasing awareness about pest threats and management though information sources external to social networks (e.g. media, social media and extension officers; Garrett et al. (2018); Garrett (2021)).

This flexibility makes *INApest()* well-suited to sit within highly integrative biosecurity planning systems, such as the "One Biosecurity" framework (Hulme et al. 2023). *INApest()* is able to incorporate information provided by rapid pest spread model parameterisation frameworks (e.g. IBRAM; Jamieson et al. (2022)) and complex natural dispersal processes, such as directional spread (upstream to downstream or with prevailing wind; Planchuelo et al. (2016)) or through biotic dispersal vectors (e.g. fruit-eating birds). It can also incorporate detailed information on human, livestock or other transport movements (Mason et al. 2021) and transport networks (Seebens et al. 2019; Rocabert et al. 2024) which influence human-aided pest dispersal.

Impact assessment has been highlighted as an important, often neglected aspect of pest simulation frameworks (Hulme et al. 2023). The outputs provided by *INApest()*, by tracking invasion and management status of individual farms in individual years permit estimation of impacts including management costs, decreases in agricultural production, biodiversity and social or cultural ecosystem values.

While *INApest()* does not explicitly include local population dynamics (rate of increase, carrying capacity and propagule production) in modelling spread or impacts, these can be included in calculating dispersal probabilities contained within adjacent matrices. A separate function - *INApestMeta()*[3] - is available which demonstrates that it is possible to implement a metapopulation model tracking local populations and propagule production within a simulation framework that retains all the functionality provided by *INApest()*, which has been parameterised for the invertebrate pest *Tetranychus evansi* (tomato red spider mite) in New Zealand. The ability to model local populations and propagule production may be particularly important where pest reproduction rates vary considerably (terrestrial arthropods, Hulme (2017)) and where impacts and dispersal are strongly influenced by local population density. Collectively, *INApest()* and *INApestMeta()* provide flexibility to adapt scenario analyses to the level of information available on pest invasive ecology.

Conclusion

Integrating global change and social factors in realistically complex management frameworks may overcome barriers to use of scenario analyses in pest response prioritisation and planning. Our approach to invasive species scenario analysis provides users with a means to understand the levers that managers can pull and how they might interact to influence the success of pest management responses.

3 https://github.com/manaakiwhenua/SleeperPests/blob/main/INApest%20INapestMeta%20core%20function%20code/INApestMeta.r.

Additional information

Conflict of interest

The authors have declared that no competing interests exist.

Ethical statement

No ethical statement was reported.

Use of AI

No use of AI was reported.

Funding

No funding was reported.

Author contributions

Conceptualization: NWHM, GB, CEB, KAG. Data curation: CEB, NWHM. Formal analysis: NWHM, CEB. Funding acquisition: NWHM. Methodology: KAG, GB, NWHM. Project administration: NWHM. Writing - original draft: CM, NWHM, CEB. Writing - review and editing: GB, KAG, NWHM.

Author ORCIDs

Christopher E. Buddenhagen https://orcid.org/0000-0002-3016-1054
Christopher McGrannachan https://orcid.org/0000-0003-3968-2646
Graeme Bourdôt https://orcid.org/0000-0002-6361-8647
Karen A. Garrett https://orcid.org/0000-0002-6578-1616
Geoff Kaine https://orcid.org/0000-0001-6747-7434
Norman W. H. Mason https://orcid.org/0000-0002-6445-4285

Data availability

All of the data that support the findings of this study are available in the main text or Supplementary Information.

References

Adiga A, Palmer N, Baek YY, Mortveit H, Ravi SS (2022) Network models and simulation analytics for multi-scale dynamics of biological invasions. Frontiers in Big Data 5: 796897. https://doi.org/10.3389/fdata.2022.796897

Andersen KF, Buddenhagen CE, Rachkara P, Gibson R, Kalule S, Phillips D, Garrett KA (2019) Modeling epidemics in seed systems and landscapes to guide management strategies: The case of sweet potato in northern Uganda. Phytopathology 109: 1519–1532. https://doi.org/10.1094/PHYTO-03-18-0072-R

Bagavathiannan MV, Beckie HJ, Chantre GR, Gonzalez-Andujar JL, Leon RG, Neve P, Poggio SL, Schutte BJ, Somerville GJ, Werle R, Acker RV (2020) Simulation models on the ecology and management of arable weeds: Structure, quantitative insights, and applications. Agronomy 10: 1611. https://doi.org/10.3390/agronomy10101611

Beaury EM, Fusco EJ, Allen JM, Bradley BA (2021) Plant regulatory lists in the United States are reactive and inconsistent. Journal of Applied Ecology 58: 1957–1966. https://doi.org/10.1111/1365-2664.13934

Behr DM, Ozgul A, Cozzi G (2017) Combining human acceptance and habitat suitability in a unified socio-ecological suitability model: a case study of the wolf in Switzerland. Journal of Applied Ecology 54: 1919–1929. https://doi.org/10.1111/1365-2664.12880

Bell M (2006) Spread of Chilean needle grass (*Nassella neesiana*) in Marlborough New Zealand. New Zealand Plant Protection 59: 266–270. https://doi.org/10.30843/nzpp.2006.59.4417

Bodeker G, Tait A, Morgenstern O, Noone D, Revell L, McDonald A, Cullen N, Renwick J, Katurji M (2022) Aotearoa New Zealand climate change projections guidance: interpreting the latest IPCC WG1 report findings. MInistry for the Environment, Wellington, New Zealand, 51 pp.

Bourdôt G (2010) Chilean needle grass (*Nassella neesiana*) – a review of the scientific and technical literature. AgResearch Ltd., Lincoln, New Zealand. Report to the Chilean Needle Grass Action Group, 18 pp.

Bourdôt GW, Buddenhagen CE (2023) The cost of doing nothing about a sleeper weed–Nassella neesiana in New Zealand. PLoS ONE 18: e0295574. https://doi.org/10.1371/journal.pone.0295574

Bourdôt GW, Hurrell GA (1989) Cover of *Stipa neesiana* Trin. & Rupr. (Chilean needle grass) on agricultural and pastoral land near Lake Grassmere, Marlborough. New Zealand. Journal of Botany 27: 415–420. https://doi.org/10.1080/0028825X.1989.10414122

Bourdôt GW, Lamoureaux SL, Watt MS, Manning LK, Kriticos DJ (2012) The potential global distribution of the invasive weed *Nassella neesiana* under current and future climates. Biological Invasions 14: 1545–1556. https://doi.org/10.1007/s10530-010-9905-6

Bourdôt G, Basse B, Kriticos D, Dodd M (2015) Cost-benefit analysis blueprint for regional weed management: *Nassella neesiana* (Chilean needle grass) as a case study. New Zealand Journal of Agricultural Research 58: 325–338. https://doi.org/10.1080/00288233.2015.1037460

Buddenhagen CE, Tye A (2015) Lessons from successful plant eradications in Galapagos: Commitment is crucial. Biological Invasions 17: 2893–2912. https://doi.org/10.1007/s10530-015-0919-y

Buddenhagen CE, Hernandez Nopsa JF, Andersen KF, Andrade-Piedra J, Forbes GA, Kromann P, Thomas-Sharma S, Useche P, Garrett KA (2017) Epidemic network analysis for mitigation of invasive pathogens in seed systems: Potato in Ecuador. Phytopathology 107: 1209–1218. https://doi.org/10.1094/PHYTO-03-17-0108-FI

Buddenhagen CE, Rubenstein JM, Hampton JG, Rolston MP (2021) The phytosanitary risks posed by seeds for sowing trade networks. PLoS ONE 16: e0259912. https://doi.org/10.1371/journal.pone.0259912

Buddenhagen CE, Bourdot G, Mason N (2024) Chilean needle grass: Impacts of Cyclone Gabrielle on Chilean needle grass dispersal and distribution. AgResearch, 15 pp. https://doi.org/10.57935/AGR.26018665.v1 [December 18, 2024]

Capinha C, Essl F, Porto M, Seebens H (2023) The worldwide networks of spread of recorded alien species. Proceedings of the National Academy of Sciences of the United States of America 120: e2201911120. https://doi.org/10.1073/pnas.2201911120

Carlin TF, Herron DA, Buddenhagen CE, Mason NWH, Meurisse N (2025) Modelling vehicles as vectors of forest pest and pathogen spread. Journal of Forestry Research 36: 134. https://doi.org/10.1007/s11676-025-01931-x

Chapman D, Purse BV, Roy HE, Bullock JM (2017) Global trade networks determine the distribution of invasive non-native species. Global Ecology and Biogeography 26: 907–917. https://doi.org/10.1111/geb.12599

Chen T, Guestrin C (2016) XGBoost: A scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining. San Francisco, California, USA, 785–794. https://doi.org/10.1145/2939672.2939785

Connor HE, Edgar E, Bourdôt GW (1993) Ecology and distribution of naturalised species of *Stipa* in New Zealand. New Zealand Journal of Agricultural Research 36: 301–307. https://doi.org/10.1080/00288233.1993.10417727

Cope RC, Ross JV, Wittmann TA, Watts MJ, Cassey P (2019) Predicting the risk of biological invasions using environmental similarity and transport network connectedness. Risk Analysis 39: 35–53. https://doi.org/10.1111/risa.12870

Diagne C, Leroy B, Vaissière A-C, Gozlan RE, Roiz D, Jarić I, Salles J-M, Bradshaw CJA, Courchamp F (2021) High and rising economic costs of biological invasions worldwide. Nature 592: 571–576. https://doi.org/10.1038/s41586-021-03405-6

DiRenzo GV, Hanks E, Miller DAW (2023) A practical guide to understanding and validating complex models using data simulations. Methods in Ecology and Evolution 14: 203–217. https://doi.org/10.1111/2041-210X.14030

Epanchin-Niell RS, Hastings A (2010) Controlling established invaders: Integrating economics and spread dynamics to determine optimal management. Ecology Letters 13: 528–541. https://doi.org/10.1111/j.1461-0248.2010.01440.x

Etherton BA, Choudhury RA, Alcalá-Briseño RI, Xing Y, Plex Sulá AI, Carrillo D, Wasielewski J, Stelinski LL, Grogan KA, Ballen F, Blare T, Crane J, Garrett KA (2023) Are avocados toast? A framework to analyze decision-making for emerging epidemics, applied to laurel wilt. Agricultural Systems 206: 103615. https://doi.org/10.1016/j.agsy.2023.103615

Etherton BA, Plex Sulá AI, Mouafo-Tchinda RA, Kakuhenzire R, Kassaye HA, Asfaw F, Kosmakos VS, McCoy RW, Xing Y, Yao J, Sharma K, Garrett KA (2025) Translating Ethiopian potato seed networks: Identifying strategic intervention points for managing bacterial wilt and other diseases. Agricultural Systems 222: 104167. https://doi.org/10.1016/j.agsy.2024.104167

Ferrari JR, Preisser EL, Fitzpatrick MC (2014) Modeling the spread of invasive species using dynamic network models. Biological Invasions 16: 949–960. https://doi.org/10.1007/s10530-013-0552-6

Fontan R, Perez CM, Adhikari A, Mouafo-Tchinda RA, Plex Sulá AI, Robledo J, Etherton BA, Choudhary M, Sarwar MA, Afzal Naveed Z, and Garrett KA (2025) MetaQuestion: A web application for expert knowledge elicitation addressing plant health and applied plant ecology. arXiv:2509.19393.

Frost CM, Allen WJ, Courchamp F, Jeschke JM, Saul W-C, Wardle DA (2019) Using network theory to understand and predict biological invasions. Trends in Ecology & Evolution 34(9): 831–843. https://doi.org/10.1016/j.tree.2019.04.012

Gallien L, Münkemüller T, Albert CH, Boulangeat I, Thuiller W (2010) Predicting potential distributions of invasive species: Where to go from here? Diversity & Distributions 16: 331–342. https://doi.org/10.1111/j.1472-4642.2010.00652.x

Garrett KA (2021) Impact network analysis and the INA R package: Decision support for regional management interventions. Methods in Ecology and Evolution 12: 1634–1647. https://doi.org/10.1111/2041-210X.13655

Garrett KA, Alcalá-Briseño RI, Andersen KF, Buddenhagen CE, Choudhury RA, Fulton JC, Hernandez Nopsa JF, Poudel R, Xing Y (2018) Network analysis: A systems framework to address grand challenges in plant pathology. Annual Review of Phytopathology 56: 559–580. https://doi.org/10.1146/annurev-phyto-080516-035326

Green DG (2023) Emergence in complex networks of simple agents. Journal of Economic Interaction and Coordination 18: 419–462. https://doi.org/10.1007/s11403-023-00385-w

Hester SM, Cacho OJ (2017) The contribution of passive surveillance to invasive species management. Biological Invasions 19: 737–748. https://doi.org/10.1007/s10530-016-1362-4

Howell CJ (2012) Progress toward environmental weed eradication in New Zealand. Invasive Plant Science and Management 5: 249–258. https://doi.org/10.1614/IPSM-D-11-00001.1

Hughes G, Madden LV (2002) Some methods for eliciting expert knowledge of plant disease epidemics and their application in cluster sampling for disease incidence. Crop Protection 21: 203–215. https://doi.org/10.1016/S0261-2194(01)00087-4

Hulme PE (2009) Trade, transport and trouble: Managing invasive species pathways in an era of globalization. Journal of Applied Ecology 46: 10–18. https://doi.org/10.1111/j.1365-2664.2008.01600.x

Hulme PE (2017) Climate change and biological invasions: Evidence, expectations, and response options. Biological Reviews of the Cambridge Philosophical Society 92: 1297–1313. https://doi.org/10.1111/brv.12282

Hulme PE, Beggs JR, Binny RN, Bray JP, Cogger N, Dhami MK, Finlay-Smits SC, French NP, Grant A, Hewitt CL, Jones EE, Lester PJ, Lockhart PJ (2023) Emerging advances in biosecurity to underpin human, animal, plant, and ecosystem health. iScience 26: 107462. https://doi.org/10.1016/j.isci.2023.107462

IPBES (2023) Summary for policymakers of the thematic assessment report on invasive alien species and their control of the intergovernmental science-policy platform on biodiversity and ecosystem services. In: Roy HE, Pauchard A, Stoett P, Renard Truong T, Bacher S, Galil BS, Hulme PE, Ikeda T, Sankaran KV, McGeoch MA, Meyerson LA, Nuñez MA, Ordonez A, Rahlao SJ, Schwindt E, Seebens H, Sheppard AW, Vandvik V (Eds) IPBES Secretariat, Bonn, Germany, 41. https://doi.org/10.5281/zenodo.7430692

IPCC [Ed.] (2000) Emissions scenarios: summary for policymakers; a special report of IPCC Working Group III. Intergovernmental Panel on Climate Change, 20 pp.

James TK, Dowsett CA, Trolove MR (2015) Identification and enumeration of weed seeds in chopped maize being transported for silage. New Zealand Plant Protection 68: 118–123. https://doi.org/10.30843/nzpp.2015.68.5879

Jamieson LE, Woodberry O, Mascaro S, Meurisse N, Jaksons R, Brown SDJ, Ormsby M (2022) An integrated biosecurity risk assessment model (IBRAM) for evaluating the risk of import pathways for the establishment of invasive species. Risk Analysis 42: 1325–1345. https://doi.org/10.1111/risa.13861

Jeger MJ, Pautasso M, Holdenrieder O, Shaw MW (2007) Modelling disease spread and control in networks: Implications for plant sciences. The New Phytologist 174: 279–297. https://doi.org/10.1111/j.1469-8137.2007.02028.x

Kaine G, Wright V (2022) Attitudes, involvement and public support for pest control methods. Conservation 2: 566–586. https://doi.org/10.3390/conservation2040038

Kelly JE, Quinn JC, Nielsen SG, Weston P, Broster JC, Weston LA (2020) Causative factors influencing epizoochorous dispersal of weed seeds by sheep and associated carcass contamination in southern Australia. Weed Research 60: 221–231. https://doi.org/10.1111/wre.12415

Kriticos D, Lamoureaux S, Bourdôt G, Pettit W (2004) Nassella tussock: Current and potential distribution in New Zealand. New Zealand Plant Protection 57: 81–88. https://doi.org/10.30843/nzpp.2004.57.6976

Kriticos D, Maywald G, Yonow T, Zurcher E, Herrmann N, Sutherst R (2015). CLIMEX. Version 4. Exploring the Effects of Climate on Plants, Animals and Diseases.

Leung B, Roura-Pascual N, Bacher S, Heikkilä J, Brotons L, Burgman MA, Dehnen-Schmutz K, Essl F, Hulme PE, Richardson DM, Sol D, Vilà M (2012) TEASIng apart alien species risk assessments: A framework for best practices. Ecology Letters 15: 1475–1493. https://doi.org/10.1111/ele.12003

Li Y, Liu X, Zeng H, Zhang J, Zhang L (2021) Public education improves farmers knowledge and management of invasive alien species. Biological Invasions 23(6): 2003–2017. https://doi.org/10.1007/s10530-021-02486-8

Liew ECY, Phelan M, McDougall KL (2023) The efficacy of a range of hygiene measures for boot cleaning to protect natural vegetation from Phytophthora cinnamomi. Scientific Reports 13(1): 5825. https://doi.org/10.1038/s41598-023-32681-7

Lustig A, Worner SP, Pitt JPW, Doscher C, Stouffer DB, Senay SD (2017) A modeling framework for the establishment and spread of invasive species in heterogeneous environments. Ecology and Evolution 7: 8338–8348. https://doi.org/10.1002/ece3.2915

Maher J, Virtue J, Stringham OC, Cassey P (2024) Discrepancies in Australian jurisdiction-based regulation of invasive plants. Invasive Plant Science and Management 17: 267–280. https://doi.org/10.1017/inp.2024.26

Marchioro CA, Krechemer FS (2021) Prevention is better than cure: Integrating habitat suitability and invasion threat to assess global biological invasion risk by insect pests under climate change. Pest Management Science 77: 4510–4520. https://doi.org/10.1002/ps.6486

Mason NWH (2023) INApest and INApestmeta core function code. https://github.com/manaaki-whenua/SleeperPests/tree/main/INApest%20INApestMeta%20core%20function%20code

Mason W, Cuttance E, Madin B, Sadler R, Cowled B, Stevenson M, Firestone S, Pfeiffer C (2021) Analyses of New Zealand stock movement data. Biosecurity New Zealand, 79 pp. https://www.mpi.govt.nz/dmsdocument/49114-Analysis-of-New-Zealand-Stock-Movement-Data

Mason NWH, Kirk NA, Price RJ, Law R, Bowman R, Sprague RI (2023) Science for social licence to arrest an ecosystem-transforming invasion. Biological Invasions 25: 873–888. https://doi.org/10.1007/s10530-022-02953-w

McGrannachan CM, Pagad S, McGeoch MA (2021) A multiregional assessment of transnational pathways of introduction. NeoBiota 64: 43–67. https://doi.org/10.3897/neobiota.64.60642

Ministry for the Environment (2018) Climate change projections for New Zealand: Atmosphere projections based on simulations from the IPCC fifth assessment. Wellington, New Zealand, 131 pp. https://environment.govt.nz/assets/Publications/Files/Climate-change-projections-2nd-edition-final.pdf

Nathan R, Katul GG, Bohrer G, Kuparinen A, Soons MB, Thompson SE, Trakhtenbrot A, Horn HS (2011) Mechanistic models of seed dispersal by wind. Theoretical Ecology 4(2): 113–132. https://doi.org/10.1007/s12080-011-0115-3

Nathan R, Klein E, Robledo-Arnuncio JJ, Revilla E (2012). Dispersal kernels: review. In: Clobert J, Baguette M, Benton TG, Bullock JM (Eds) Dispersal Ecology and Evolution, Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199608898.003.0015

Panetta FD (2004) Seed banks: the bane of the weed eradicator. In: Sindel B, Johnson S (Eds) Proceedings of the 14th Australian Weeds Conference. Weed Society of New South Wales, Wagga Wagga, New South Wales, Australia, 523–526.

Panetta FD (2009) Weed eradication-An economic perspective. Invasive Plant Science and Management 2: 360–368. https://doi.org/10.1614/IPSM-09-003.1

Panetta FD (2015) Weed eradication feasibility: lessons of the 21st century. Weed Research 55: 226–238. https://doi.org/10.1111/wre.12136

Panetta FD, Lawes R (2005) Evaluation of weed eradication programs: the delimitation of extent: Evaluation of weed eradication programs. Diversity & Distributions 11: 435–442. https://doi.org/10.1111/j.1366-9516.2005.00179.x

Panetta FD, Lawes R (2007) Evaluation of the Australian branched broomrape (*Orobanche ramosa*) eradication program. Weed Science 55: 644–651. https://doi.org/10.1614/WS-07-058.1

Panetta FD, Cacho O, Hester S, Sims-Chilton N, Brooks S (2011) Estimating and influencing the duration of weed eradication programmes. Journal of Applied Ecology 48: 980–988. https://doi.org/10.1111/j.1365-2664.2011.02000.x

Parry HR, Sadler R, Kriticos DJ (2013) Practical guidelines for modelling post-entry spread in invasion ecology. NeoBiota 18: 41–66. https://doi.org/10.3897/neobiota.18.4305

Pautasso M, Jeger MJ (2014) Network epidemiology and plant trade networks. AoB Plants 6: plu007. https://doi.org/10.1093/aobpla/plu007

Pautasso M, Xu X, Jeger MJ, Harwood TD, Moslonka-Lefebvre M, Pellis L (2010a) Disease spread in small-size directed trade networks: The role of hierarchical categories. Journal of Applied Ecology 47: 1300–1309.

Pautasso M, Dehnen-Schmutz K, Holdenrieder O, Pietravalle S, Salama N, Jeger MJ, Lange E, Hehl-Lange S (2010b) Plant health and global change - some implications for landscape management. Biological Reviews 85(4): 729–755. https://doi.org/10.1111/j.1469-185X.2010.00123.x

Phillips CB, Kean JM, Vink CJ, Berry JA (2018) Utility of the CLIMEX 'match climates regional' algorithm for pest risk analysis: An evaluation with non-native ants in New Zealand. Biological Invasions 20: 777–791. https://doi.org/10.1007/s10530-017-1574-2

Planchuelo G, Catalán P, Delgado JA (2016) Gone with the wind and the stream: Dispersal in the invasive species *Ailanthus altissima.* Acta Oecologica 73: 31–37. https://doi.org/10.1016/j.actao.2016.02.006

Plex Sulá AI, Keshav K, Adhikari A, Mouafo-Tchinda RA, Robledo J, Shah SN, Garrett KA (2025). geohabnet: An R package for mapping habitat connectivity for biosecurity and conservation. arXiv:2510.24955.

Pluess T, Jarošík V, Pyšek P, Cannon R, Pergl J, Breukers A, Bacher S (2012) Which factors affect the success or failure of eradication campaigns against alien species? PLoS ONE 7: e48157. https://doi.org/10.1371/journal.pone.0048157

Reeve IJ, Kaine G, Lees JW, Barclay E (2000) Producer perceptions of pasture decline and grazing management. Australian Journal of Experimental Agriculture 40: 331. https://doi.org/10.1071/EA98018

Renteria JL, Rouget M, Visser V (2017) Rapid prioritization of alien plants for eradication based on climatic suitability and eradication feasibility. Austral Ecology 42: 995–1005. https://doi.org/10.1111/aec.12528

Rickowski FS, Ruland F, Bodin Ö, Evans T, Fowler MS, Kluger LC, Latombe G, Lenzner B, Macêdo RL, Adriaens T, Arlinghaus R, Castellanos-Galindo GA, Dick JTA, Dickey JWE, Essl F, Gallardo B, Hilt S, Itescu Y, Jarić I, Kimmig S, Kumar L, Novoa A, Oficialdegui FJ, Pérez-Granados C, Pyšek P, Rabitsch W, Richardson DM, Roura-Pascual N, von Schmalensee M, Yannelli FA, Vilà M, Vimercati G, Jeschke JM (2025) A Systems Perspective: How Social–Ecological Networks Can Improve Our Understanding and Management of Biological Invasions. BioScience.

Robledo J, Sulá AIP, Jaworski LG, Mouafo-Tchinda RA, Andersen Onofre KF, Thomas-Sharma S, Garrett KA (2025). Expert Knowledge Elicitation: Accessing the Big Data in Experts' Brains. Phytopathology® 115: 1245-1259. https://doi.org/10.1094/PHYTO-06-25-0220-FI

Rocabert C, Fenet S, Kaufmann B, Gippet JMW (2024) Accounting for the topology of road networks to better explain human-mediated dispersal in terrestrial landscapes. Ecography 2024: e07068. https://doi.org/10.1111/ecog.07068

Roigé M, Phillips CB (2021) Validation and uncertainty analysis of the match climates regional algorithm (CLIMEX) for Pest risk analysis. Ecological Informatics 61: 101196. https://doi.org/10.1016/j.ecoinf.2020.101196

Runghen R, Llopis-Belenguer C, McNeill MR, Dalla Riva GV, Stouffer DB (2023) Using network analysis to study and manage human-mediated dispersal of exotic species. Biological Invasions 25: 3369–3389. https://doi.org/10.1007/s10530-023-03122-3

Saffer A, Jones C, Horner E, Laginhas B, Polo J, Seliger B, Sanchez F, Worm T, Meentemeyer R (2025) Quantifying uncertainty in forecasts of when and where invasions happen. Biological Invasions 27: 117. https://doi.org/10.1007/s10530-025-03573-w

Sankaran K, Schwindt E, Sheppard AW, Foxcroft LC, Vanderhoeven S, Egawa C, Peacock L, Castillo ML, Zenni RD, Müllerová J, González Martínez AI, Bukombe JK, Wanzala W, Mangwa DC (2023) IPBES Invasive Alien Species Assessment: Chapter 5. Management; challenges, opportunities and lessons learned. Zenodo. https://doi.org/10.5281/ZENODO.7430733

Sanson RL (2000) Agribase – Introduction and history. Proceedings of the New Zealand Veterinary Association Epidemiology and Animal Health Management Branch Seminar, Wallaceville, Upper Hutt, New Zealand, 23-24 November 2000. Massey University, Wallaceville, Upper Hutt, New Zealand, 61–64.

Saunders JT, Greer G, Bourdôt G, Saunders C, James T, Rolando C, Monge J, Watt MS (2017) The economic costs of weeds on productive land in New Zealand. International Journal of Agricultural Sustainability 15: 380–392. https://doi.org/10.1080/14735903.2017.1334179

Sayles JS, Mancilla Garcia M, Hamilton M, Alexander SM, Baggio JA, Fischer AP, Ingold K, Meredith GR, Pittman J (2019) Social-ecological network analysis for sustainability sciences: A systematic review and innovative research agenda for the future. Environmental Research Letters 14: 093003. https://doi.org/10.1088/1748-9326/ab2619

Schelhas J, Alexander J, Brunson M, Cabe T, Crall A, Dockry MJ, Emery MR, Frankel SJ, Hapner N, Hickman CR, Jordan R, LaVoie MJ, Ma Z, Starinchak J, Vukomanovic J (2021) Social and Cultural Dynamics of Non-native Invasive Species. In: Poland TM, Patel-Weynand T, Finch DM, Miniat CF, Hayes DC, Lopez VM (Eds) Invasive Species in Forests and Rangelands of the United States: A Comprehensive Science Synthesis for the United States Forest Sector. Cham, Springer International Publishing, 267-291. https://doi.org/10.1007/978-3-030-45367-1_12

Schläpfer M, Dong L, O'Keeffe K, Santi P, Szell M, Salat H, Anklesaria S, Vazifeh M, Ratti C, West GB (2021) The universal visitation law of human mobility. Nature 593(7860): 522–527. https://doi.org/10.1038/s41586-021-03480-9

Seebens H, Briski E, Ghabooli S, Shiganova T, MacIsaac HJ, Blasius B (2019) Non-native species spread in a complex network: The interaction of global transport and local population dynamics determines invasion success. Proceedings. Biological Sciences 286: 20190036. https://doi.org/10.1098/rspb.2019.0036

Simberloff D (2009) Eradication—Preventing invasions at the outset. Weed Science 51: 247–253. https://doi.org/10.1614/0043-1745(2003)051[0247:EPIATO]2.0.CO;2

Simberloff D, Keitt B, Will D, Holmes N, Pickett E, Genovesi P (2018) Yes We Can! Exciting Progress and Prospects for Controlling Invasives on Islands and Beyond. Western North American Naturalist 78: 942. https://doi.org/10.3398/064.078.0431

Sutherst R (1985) A computerised system for matching climates in ecology. Agriculture, Ecosystems & Environment 13: 281–299. https://doi.org/10.1016/0167-8809(85)90016-7

Tamme R, Götzenberger L, Zobel M, Bullock JM, Hooftman DAP, Kaasik A, Pärtel M (2014) Predicting species' maximum dispersal distances from simple plant traits. Ecology 95: 505–513. https://doi.org/10.1890/13-1000.1

Tischendorf L, Fahrig L (2000) On the usage and measurement of landscape connectivity. Oikos 90: 7–19. https://doi.org/10.1034/j.1600-0706.2000.900102.x

Urban D, Keitt T (2001) Landscape connectivity: A graph-theoretic perspective. Ecology 82: 1205–1218. https://doi.org/10.1890/0012-9658(2001)082[1205:LCAGTP]2.0.CO;2

van Klinken RD, Kingham L, Hill MP, Collins K (2023) A menu of measures to manage trade-related plant pest risks, and a review of methods for demonstrating measure efficacy. Biological Invasions 25: 1227–1248. https://doi.org/10.1007/s10530-022-02977-2

Walther G-R, Roques A, Hulme PE, Sykes MT, Pyšek P, Kühn I, Zobel M, Bacher S, Botta-Dukát Z, Bugmann H (2009) Alien species in a warmer world: Risks and opportunities. Trends in Ecology & Evolution 24: 686–693. https://doi.org/10.1016/j.tree.2009.06.008

Wichmann MC, Alexander MJ, Soons MB, Galsworthy S, Dunne L, Gould R, Fairfax C, Niggemann M, Hails RS, Bullock JM (2009) Human-mediated dispersal of seeds over long distances. Proceedings. Biological Sciences 276: 523–532. https://doi.org/10.1098/rspb.2008.1131

Wiebe K, Zurek M, Lord S, Brzezina N, Gabrielyan G, Libertini J, Loch A, Thapa-Parajuli R, Vervoort J, Westhoek H (2018) Scenario development and foresight analysis: Exploring options to inform choices. Annual Review of Environment and Resources 43: 545–570. https://doi.org/10.1146/annurev-environ-102017-030109

Will H, Tackenberg O (2008) A mechanistic simulation model of seed dispersal by animals. Journal of Ecology 96(5): 1011–1022. https://doi.org/10.1111/j.1365-2745.2007.01341.x

Wilson RS, Hooker N, Tucker M, LeJeune J, Doohan D (2009) Targeting the farmer decision making process: A pathway to increased adoption of integrated weed management. Crop Protection 28: 756–764. https://doi.org/10.1016/j.cropro.2009.05.013

Yang K, Li J, Liu M, Lei T, Xu X, Wu H, Cao J, Qi G (2023) Complex systems and network science: A survey. Journal of Systems Engineering and Electronics 34: 543–573. https://doi.org/10.23919/JSEE.2023.000080

Xing Y, Hernandez Nopsa JF, Andersen KF, Andrade-Piedra JL, Beed FD, Blomme G, Carvajal-Yepes M, Coyne DL, Cuellar WJ, Forbes GA, Kreuze JF, Kroschel J, Kumar PL, Legg JP, Parker M, Schulte-Geldermann E, Sharma K, Garrett KA (2020) Global Cropland Connectivity: A Risk Factor for Invasion and Saturation by Emerging Pathogens and Pests. BioScience 70: 744-758. https://doi.org/10.1093/biosci/biaa067

Yletyinen J, Perry GLW, Burge OR, Mason NWH, Stahlmann-Brown P (2021) Invasion landscapes as social-ecological systems: Role of social factors in invasive plant species control. People and Nature 3: 795–810. https://doi.org/10.1002/pan3.10217

Supplementary material 1

Status of Chilean needle grass invasion in NZ

Authors: Christopher E. Buddenhagen, Christopher McGrannachan, Graeme Bourdôt, Shona Lamoureaux, Karen A. Garrett, Geoff Kaine, Norman W. H. Mason

Data type: docx

Copyright notice: This dataset is made available under the Open Database License (http://opendatacommons.org/licenses/odbl/1.0/). The Open Database License (ODbL) is a license agreement intended to allow users to freely share, modify, and use this Dataset while maintaining this same freedom for others, provided that the original source and author(s) are credited.

Link: https://doi.org/10.3897/neobiota.106.161880.suppl1